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Essays in Environmental Economics and International Trade

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ABSTRACT

ESSAYS IN ENVIRONMENTAL ECONOMICS AND INTERNATIONAL TRADE

By

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The essays in this dissertation discuss modeling techniques for international trade and their application to environmental policy. In addition, I present evidence of the effect of air pollution on worker sick leave.

Chapter 1 presents an application of computable general equilibrium (CGE) modeling in environmental policy evaluation. In most CGE models, researchers assume that goods are differentiated by their origin of production, known as the Armington model of international trade. In this chapter, I consider their application to carbon taxes, carbon leakage, and border carbon adjustments (BCAs). BCAs are designed to address carbon leakage, which is a phenomenon where areas not subject to an emissions tax increase their emissions in response to regulated areas decreasing emissions. I find that the non-Armington model predicts a higher carbon leakage rate compared to typical Armington models. I also find that border rebates are more effective than border tariffs at reducing leakage.

Chapter 2 presents an application of the non-Armington model to the North American Free Trade Agreement (NAFTA). Previous studies of free trade agreements have shown that the

Armington model may underpredict changes in trade. In this chapter, I build a non-Armington model that still incorporates observable features of the international trade market. I then simulate the trade effects from NAFTA, and I compare these results to previous studies. I find that the non-Armington model can generate larger changes in trade than the Armington model.

Chapter 3 discusses how pollution might affect worker productivity, specifically the probability of taking sick leave from work. In this chapter, I evaluate these studies using a causal inference technique to quantify the impact of the CAAA on the number of days workers miss due to illness. I discuss the possible issues with using simple hazard rates for illness in making calculations of missed days and I also discuss how paid sick leave may influence results. Using a DiD framework, I find that the CAAA reduced the probability of taking a sick day in a given week by 0.1 percentage points.

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BY

KENNETH AUSTIN CASTELLANOS

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Dedication

This dissertation is dedicated to my wife, Natalie; my daughter, Zora; and my parents, Linda and Carlos, who have all supported me and given me the drive to continue during my program.

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Introduction

As research has shown the damages from climate change and air pollution, governments have begun creating policies to address these issues. In a global economy, the policies that one region enacts can have spillover effects on other regions. Additionally, determining the economic benefits from pollution reduction requires the use of empirical analysis. The first chapter of this thesis focuses on climate policy, the second chapter focuses on international trade modeling, and the last chapter focuses on policy evaluation of the Clean Air Act Amendments. I first discuss current questions in carbon policy and international trade. I then compare the predictions from my international trade model in the context of the North American Free Trade Agreement. I finish by using a causal inference model to analyze the effect of air pollution on sick leave.

When undertaking policy analysis, researchers in government and academia often make use of computable general equilibrium (CGE) modeling. This framework allows for counterfactual analysis and can incorporate rich data sources on industry supply chains. This can be especially useful in environmental and trade policy analysis, which often target specific industries. In environmental policies, emissions intensive sectors such as utilities, manufacturing, and construction are often heavily affected sectors. In trade policy, tariffs are generally targeted at highly traded manufacturing industries. CGE models provide tractable ways of evaluating policy impacts by industry and incorporating the supply chain structure in the analysis.

Most CGE models include international trade by using the Armington model. This model assumes that importers have preferences over the origin of production of goods (Armington 1969). The Armington model provides a tractable framework for incorporating several observable features of trade that are typically not present in non-Armington models. However, some researchers have pointed out problems with the predictions from the Armington model.

One such issue is that Armington models will predict finite export supply curve elasticities. The export supply curve determines the quantity exporters will supply based on the price received from importers. Recent evidence has suggested that this curve is likely perfectly elastic, even for big countries like the United States and China (Amiti, Redding, and Weinstein 2019). This relationship can be replicated in a general equilibrium model using a non-Armington framework. The first two chapters of this dissertation develop the method of using a non-Armington model to analyze government policy.

In chapter 1, I use a non-Armington model to explore how international trade and environmental policy interact. When implementing taxes on carbon, many countries may worry about the phenomenon of carbon leakage. This occurs when areas outside of the regulated country increase production (and by extension emissions) in response to reduced production in the regulated country. Some have suggested using border carbon adjustments (BCAs) to reduce carbon leakage and improve the competitiveness of the taxed country in the world market. I show that a non-Armington model predicts that leakage rates are higher, and BCAs are less effective. The smaller effectiveness of BCAs is due to the perfectly elastic export supply curve. If the importing country is unable to push down the output price of the exporting region, producers will not have an incentive to cut production.

Research has also shown that the Armington model predicts changes in trade volumes that are smaller than what is observed in the data, sometimes known as the "stuck on zero" problem (Kuiper and van Tongeren 2007). A well-known example of this is shown in Kehoe (2005), who directly compares predictions from Armington CGE models of the impacts of the North American Free Trade Agreement (NAFTA) against the data. Kehoe finds that the Armington model of trade severely underpredicted the changes in trade seen in the data.

In chapter 2, I use a non-Armington model to evaluate the impacts of NAFTA, and I compare my results against Kehoe (2005). The non-Armington model I build in this chapter incorporates many of the features in the Armington framework, and I show how these can be easily implemented using a novel algorithm that builds trade matrices. The Armington model predicts trade flows using the distribution of prices around the world, and a non-Armington model only has a single world price for each commodity. Thus, to predict trade flows in the non-Armington model, I use the distribution of quantities around the world rather than the distribution of prices. I find that the non-Armington model can generate larger changes in trade that were more consistent with the data after the implementation of NAFTA.

In chapter 3, I evaluate the effect of the Clean Air Act Amendment (CAAA) on the number of days that workers call in sick. I first discuss the difficulties in predicting the effects of less pollution on worker sick leave. Even if one can identify the reduction in days of illness (the hazard rate), other margins may make it difficult to correctly determine the impact on sick leave. For example, some workers may shift along the intensive margin and attend work while sick, or they may engage in some other mitigating behaviors. Additionally, if some workers are covered by paid sick leave policies, this relationship becomes even more confounded. To evaluate the accuracy of simulation models, I use a difference-in-difference model to determine the policy impact of the CAAA. Since, the CAAA only regulated some counties' pollution levels, and I use this geographic heterogeneity to identify a causal impact. I find that the CAAA reduced the probability of taking a sick day by 0.1 percentage points.

Using models is a wonderful way to understand complex interactions in the world and provide insight for policy. However, we must take our models to the data to ensure that we are providing a framework that can accurately describe those relationships. We must also be willing to use different models for different purposes. An overarching theme in this dissertation is an attempt to do just that. In chapters 1 and 2, I show that relationships in international trade may be better described using a non-Armington model. In chapter 3, I discuss how to evaluate the empirical predictions of air pollution simulation models. All models have strengths and weaknesses and identifying when to use a model is a crucial part of research.

Chapter 1: Carbon Policy and International Trade

1.1 Introduction

Carbon pricing initiatives have been growing, and policymakers often focus on how to implement carbon taxes efficiently. One concern has often been how international trade is affected by carbon taxes. Policymakers may be concerned from an environmental standpoint and want to know the amount of carbon leakage from implementing these policies. Leakage is a phenomenon where production (and emissions) shifts to an untaxed country. Policymakers may also be worried from an economic standpoint and look at variables such as employment and gross domestic product (GDP) impacts. When analyzing the economic impact of these policies, governments and researchers often use computable general equilibrium (CGE) modeling to predict how a domestic policy will impact trade. CGE models typically employ the Armington model of international trade, which assumes that goods are differentiated by origin of production. In this paper, I investigate how removing the Armington assumption affects predictions in CGE modeling of climate policy.

Recent carbon pricing proposals by politicians in the United States (US) and European Union (EU) have often included border carbon adjustments (BCAs), which are policies designed to increase the price of imports from countries without carbon prices and rebate domestic producers for carbon taxes paid in production when they export to countries without carbon prices (Morris, 2018; Hafstead, 2019). Some researchers have questioned their effectiveness from a welfare standpoint (Kortum and Weisbach, 2017; Fullerton, Baylis, and Karney, 2013). However, most CGE models have predicted that BCAs are effective at reducing carbon leakage. A survey of 11 CGE models found that models predicted BCAs reduce leakage for the United

States (US) by about 30% on average, with some predicting a more than 50% reduction (Böhringer, Balisteri, and Rutherford 2012).

Most models used to study BCAs make use of the Armington model of international trade. The Armington model was developed by Paul Armington in 1969 and is still a popular way of modeling trade in environmental trade models half a century later (Armington 1969). The primary reason for using the Armington model is that it predicts three established features of international trade markets: imperfect specialization, home bias, and cross-hauling. Imperfect specialization is the observation that countries do not perfectly specialize like in the classical Ricardian comparative advantage model. Home bias is the observation that countries tend to buy more from domestic sources than international ones. Cross-hauling is the observation that countries import and export the same product category. These features were absent in the traditional trade models of Armington's time, the Ricardian model, and its variant, the Heckscher-Ohlin (HO) model.

While the Armington model is a useful model for incorporating real-world trade patterns, it also predicts a finite export elasticity. This means that when a country puts a tariff on an import, the exporting country will experience a decrease in the market price for their output. In other words, the exporter and importer share the burden of the tariff. Recent evidence from the trade war between the US and China, however, have shown that the entire burden of a tariff falls on the importer. This is consistent with a perfectly elastic export supply curve (Amiti, Redding, and Weinstein 2019). To incorporate this observation into my analysis, I specify a non-Armington small economy model, which generates perfectly elastic supply curves (Clarete and Roumasset 1987).

Only a few papers have considered environmental policy using models other than Armington trade. A recent paper used two non-Armington models to examine carbon leakage: a HO model and an imperfect competition model (Balistreri, Böhringer, and Rutherford 2018). Another paper uses a similar imperfect competition model to look at BCAs (Balistreri and Rutherford 2012). In both papers, the authors find that non-Armington models predict higher leakage rates, which is a result I confirm in this paper. I extend this literature by considering BCA policies in a perfectly competitive non-Armington framework. This model also differs by including a gravity framework in explaining trade flows. I also explore why the Armington assumption may overstate production changes abroad due to how it allocates the burden of a tariff.

The purpose of this chapter is to examine the effects of carbon policy under a model that does not invoke the Armington assumption or imperfect competition. To do this, I develop a CGE model that allows for goods to be homogenous by origin of production and predicts trade flows using a gravity model. I assume firms in each region have access to unique supply chain technology and labor markets. This approach is useful because data is readily available to calibrate the model; builders only need an environmentally extended social accounting matrix and parameter estimates from previous literature. My model employs a solution method based on a neoclassical Arrow-Debreu economy that allows markets to clear on global prices (Feltenstein and Plassmann 2008). I extend previous non-Armington CGE models to include trade flows predicted by a gravity equation, which allows me to incorporate essential features of trade in a homogeneous representative firm model.

I find that leakage from carbon taxes is higher in my non-Armington model than in most previous Armington models, which confirms earlier work on this topic. I extend the literature to show how the structure of BCAs become important for their impact on leakage. Specifically, a tariff increases leakage rates, and a rebate decreases them. A tariff does not decrease leakage rates because the tariff imposing country has very little effect on the world price. As a result, they are unable to incentivize foreign producers to reduce their output. A typical BCA is a combination of a tariff and a border rebate. The tariff is for carbon used to make an import in an untaxed country, and the rebate is for carbon taxes paid to make an export to an untaxed country. I find that these policies roughly offset each other so BCAs have a smaller effect on leakage than in Armington models. BCAs also have almost no effect on economic variables such as the aggregate labor supply, aggregate wage rate, and gross domestic product (GDP). I also explore how my assumptions about trade flows and parameters affect predictions about emissions and economic variables. However, even under many different calibrations, I still find that BCAs only modestly decrease carbon leakage on average. In general, I find that the Armington assumption is crucial to our predictions about the effects of carbon policy and border adjustments.

In the next section, I show the model construction for production, households, and government. I also explain how the model predicts trade flows and how it differs from the traditional Armington framework. In section 1.3, I discuss the dataset and parameter choices for the model application. In section 1.4, I show results from policy simulations and then explore how my parameterizations may affect the results.

1.2 Model Description

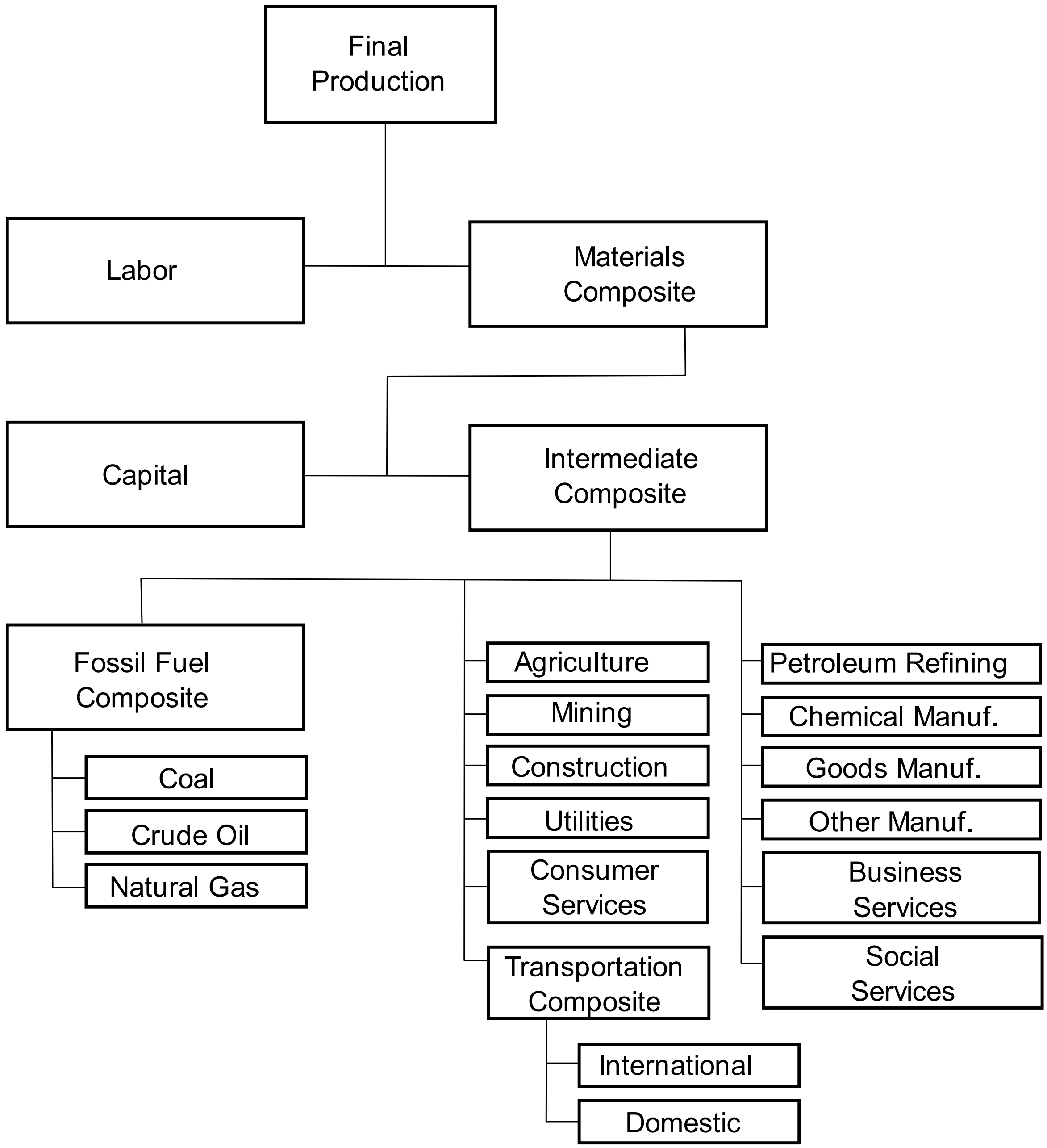
In this model, I use a Shoven and Whalley type general equilibrium structure (Shoven and Whalley 1984). One of the benefits of using CGE methodology is that common datasets, such as input-output matrices, and neoclassical functional forms allow for standardized application (Hosoe, Gasawa, and Hashimoto 2010, Dixon and Jorgenson 2012). To begin the model, I assume there are N regions, each with J representative firms. Each firm makes a single type of output distinguished by its industry (e.g., agriculture goods). If this output is traded in the international market, it is homogeneous by origin, has a single world price, and can be sold to any region. If it is non-tradable, the output is only sold domestically to buyers in the region the firm is located in.

Each region has a single representative household, a government that taxes and transfers, and a set of representative firms for each industry. I assume that utilities are the only non-tradable good, so this service has a local market price in each region. I list all the industries I use in the application in Table 1.1. I assume that labor is the only factor that is immobile between regions. This assumption is typical of Ricardian models, and researchers have observed that labor markets are generally less mobile internationally than either capital or commodity markets (Freeman 2006). I also assume that labor is sticky between industries. This assumption prevents a region from entirely specializing and moving all labor to a single industry.

1.2.a Production

I model production as a nested structure, which is common in CGE models. Figure 1.1 shows a diagram of the production process. Production is assumed to be constant returns to scale, and all firms are price-takers. The firm receives the market price for the goods they sell, and they pay market prices for any inputs. If they sell a tradable good, they receive the world price; if the firm sells a non-tradable good, they receive the regional price. Buyers may pay a domestic price that is higher than the world price for a tradable good if tariffs are levied on the product.

Figure 1.1: Organization of Production Process



Notes: This shows the production process for each firm. The process can be viewed from the bottom-up. First producers decide optimal inputs for fossil fuels and intermediate goods ad create the intermediate goods composite. This is combined with capital to create a materials composite, and finally materials and labor combine to produce a final output.

Table 1.1: List of Industries and Regions

Industries/Commodities	**Regions**
Coal Extraction[1]	China
Oil Extraction	Europe
Natural Gas Extraction[1]	North America (Canada & Mexico)
Agriculture	
Mining[2]	United States
Goods Manufacturing[2]	Rest of the World
Petroleum Refining[1]	
Chemical Manufacturing	
Other Manufacturing	
Utilities*	
Construction	
Consumer Services	
Transportation	
Business Services	
Social Services	

Notes: This is a list of industries and regions used in the model. The industries were chosen for their sensitivity to carbon taxes and aggregated from the world input-output database. Regions Europe, North America, and Rest of the World are aggregated regions from countries in the WIOD.

[1]Grouped as a carbon emitting fuel and subject to carbon tax.

[2]Considered a carbon rich production process and subject to a carbon tariff.

*Utilities are a non-tradable commodity, so they receive a regional price.

A firm solves a cost minimization problem for each nest and then uses that solution to determine optimal demands for upper nests. For example, a firm will determine the optimal mix of fossil fuels to create a fossil fuel composite. This input is an imaginary good that is simply a bundle of the optimal combination of fossil fuels in the previous nest. The fossil fuel composite is then combined with all other commodities to create the intermediate composite. The intermediate composite is then combined with capital to make the materials composite, and the materials composite is combined with labor to create a final product.

There are three nests combined using constant elasticity of substitution (CES) production functions. I define Y_{nh}^{j} as the output of composite h in region n for industry j and X_{ni}^{j} is input i in the composite for industry j in region n. The subscript h indicates which nest the firm is optimizing fossil fuel, intermediate, or materials. The index i can represent any industry in Table 1.1 or any composite formed by the firm as an input to the upper nests. For the fossil fuel nest, inputs consist of coal, crude oil, and natural gas. For the intermediate composite, inputs are the remaining goods and services listed in Table 1.1, along with the fossil fuel composite good. The materials nest takes two inputs: capital and the intermediate composite good. The producer's problem for each CES nest is defined as

$$\min \sum_{i=1}^{H} (P_{ni}^{j} + \tau_{ni}) X_{ni}^{j}$$

$$s.t.$$

$$Y_{nh}^{j} = \gamma_{nh}^{j\,\frac{\sigma_h}{\sigma_h - 1}} \left(\sum_{i=1}^{H} \alpha_{ni}^{j} X_{ni}^{j\,\frac{\sigma_h - 1}{\sigma_h}} \right)^{\frac{\sigma_h}{\sigma_h - 1}}$$

Firms minimize the cost of the composite subject to a CES production function. The price vector P_{ni}^{j} is the net price of input i to firm j in region n, which is augmented by the tax τ_{ni} on good i in region n. This tax is inclusive of any carbon taxes and tariffs. Since the composites are created within the firm, the price of a composite as an input to a higher nest can differ by industry j. However, for market goods, the firm pays the market price of the good. So, $P_{ni}^{j} = P_{ni}^{k} \forall j, k$ if i is a non-traded market good, i.e., all prices are the same for every buyer in a region for non-traded goods. If i is a traded good, then $P_{ni}^{j} = P_{mi}^{k} \forall j, k, n, m$, i.e., all firms in all regions see the same global price for traded goods. For each composite h, there are H number of inputs, so the term in parentheses is a combination of all the inputs that go into composite h. The share parameter is α_{ni}^{j} for input i and the shift parameter is γ_{nh}^{j} for composite h and both are unique by region and industry. The cost of any composite is the expenditure function evaluated at optimal demand quantities. Finally, the substitution parameter σ_h is unique to each composite or nest. Estimates for σ_h are taken from the literature, and the rest of the parameters are calibrated from a dataset on world production and trade. Equation 1 below is the input demand function for producers.

$$\frac{X_{ni}^{j}}{Y_{nh}^{j}} = \frac{{\alpha_{ni}^{j}}^{\sigma_h}\left(P_{ni}^{j} + \tau_{ni}\right)^{-\sigma_h}}{{\gamma_{nh}^{j}}^{\frac{\sigma_h}{1-\sigma_h}}\left(\sum_{i=1}^{H} {\alpha_{ni}^{j}}^{-\sigma}\left(P_{ni}^{j} + \tau_{ni}\right)^{1-\sigma_h}\right)^{\frac{-\sigma_h}{1-\sigma_h}}} \tag{1}$$

Here optimal input demand X_{ni}^{j} is expressed as a function per unit of output Y_{nh}^{j}.

Transportation costs are defined explicitly in this model. This captures emissions from transportation use and model changes in costs due to changes in trade volumes. I assume that the demand for transportation services is a function of international shipping distance and a constant domestic cost. If a firm begins exporting to further distances, their demand for transportation services increases. The production function for the transportation composite is defined:

$$Y_{n(tcomp)}^{j} = \frac{X_{n(trans)}^{j}}{\exp\left(\eta^{1} \ln\left(\frac{\sum_{z=1}^{N} F_{zn}^{j} D_{zn}}{\sum_{z=1}^{N} F_{zn}^{j}}\right) + \eta_{\mathrm{n}}^{2\mathrm{j}}\right)} \tag{2}$$

The left-hand side is the output of the transportation composite. The numerator of the right-hand side is the input demand for the transportation composite. In the denominator, the first term inside the exponentiation is the international shipping cost. The variable F_{zn}^{j} is the amount of good j that is transported from origin n to destination z, and the parameter D_{zn} is the distance between those regions. Taking the two summations together gives the average distance a commodity travels weighted by trade flows. As the average shipping distance increases, the amount of transportation services required to make a unit of the transportation composite input also increases. This relationship is determined by the slope parameter η^1. The second term in the denominator, η_n^{2j} represents the domestic cost, which I assume is constant with respect to distance.

Final production is a Cobb-Douglas combination of the materials composite and labor. The production function is specified as:

$$Q_n^j = \gamma_{pn}^j {m_n^j}^{\omega_n^j} {L_n^j}^{1-\omega_n^j}$$

Where Q_n^j , m_n^j, and L_n^j represent total output, materials composite input, and labor input, respectively, for industry j in region n. The share parameter ω_n^j and scale parameter γ_{pn}^j are calibrated using my dataset and vary by industry and region. Using first-order conditions and the expenditure function gives the demands for materials based on input prices and the industry's output price:

$$m_n^j = \left(\frac{\omega_n^j}{P_{nm}^j}\right)(P_n^j - S_n^j)Q_n^j \tag{3}$$

$$L_n^j = \left(\frac{1-\omega_n^j}{w_n^j}\right)(P_n^j - S_n^j)Q_n^j \tag{4}$$

These are common Cobb-Douglas expenditure share demand functions, where P_{nm}^j is the per-unit cost of the materials composite and w_n^j is the wage rate. The output price is P_n^j and some firms may get a per-unit subsidy of S_n^j. If good j is a tradable good, then $P_n^j = P_m^j \; \forall \; n, m,$ i.e., all regions have the same world output price. Note that this equality would not hold in an Armington model, as output prices are determined by the firm's location. Market inputs (non-composite inputs) have prices equal to the corresponding industry's output price. If j is a non-tradable good, $P_n^j = P_{nj}^k \ \forall\, j, k$, i.e., the price of market input j to firm k in region n is equal to the output price of industry j in region n. If j is a tradable good, $P^j = P_n^j = P_{mj}^k \ \forall\, j, k, n, m$, so, all firms in all regions pay the world price of output from industry j.

Equations 1-4 describe the production process for an arbitrary firm j in region n. Together they give a system of input demand equations. Intermediate input and capital demands are determined from equations 1-3 and labor demands are determined by equation 4. This is a flexible and common structure used by CGE models, and the model can be easily calibrated to baseline data using existing methods. With these equations in hand, I now turn to the household sector.

1.2.b Households

There is one representative household for each region, which owns initial endowments of capital and labor. Capital is internationally mobile, and all households can supply capital to the world market at the world price. I also make the common Ricardian assumption that households can only supply labor to the home region. Access to labor markets is partly how the model drives trade from comparative advantage.

The utility function for the household is quasi-linear between consumption and leisure and defined for each region n. The variable C_n is a Cobb-Douglas consumption composite of all goods and services, and the lowercase c_n^j is consumption of good j in region n. $\hat{P}_n$ is a price index representing the cost of a unit of aggregate consumption C_n. Note that prices are augmented by total taxes τ_{nj}, which like the producer's problem, is inclusive of all carbon taxes, tariffs, and subsidies. The variable w_n is the aggregate wage in the region, and r is the global price of capital. Each household also receives an allocation of capital $\overline{K}_n$ and a government transfer, G_n, which is determined by tax revenue.

$$U_n(C_n, l_n) = C_n + \mu_n \frac{(\overline{L}_n - l_n)^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}$$

s.t.

$$\hat{P}_n C_n = w_n l_n + r\overline{K}_n + G_n$$

where

$$C_n = \prod_{j=1}^{J} \left(c_n^j\right)^{\theta_{nj}} \text{ and } \hat{P}_n = \prod_{j=1}^{J} \left(\frac{P_n^j + \tau_{nj}}{\theta_{nj}}\right)^{\theta_{nj}}$$

Each household is allocated $\overline{L}_n$ units of labor, of which they supply l_n to the market and keep the rest as leisure. Taking FOCs and solving for the demand for leisure gives the market labor supply function.

$$l_n = \overline{L}_n - \left(\frac{w_n}{\mu_n \hat{P}_n}\right)^{\nu} \tag{5}$$

Demand for commodities is a Cobb-Douglas demand curve or fixed share of income.

$$c_n^j = \frac{\theta_n^j}{\hat{P}_n^j}\left(w_n\left[\overline{L}_n - \left(\frac{w_n}{\mu_n \hat{P}_n}\right)^{\nu}\right] + r\overline{K}_n + G_n\right) \tag{6}$$

The equations above only model aggregate labor market and consumption behavior for a region. Households must also choose the industries to which they will supply labor. In many models, labor is assumed to be perfectly mobile between industries. If labor is perfectly mobile in this model, workers will all move to the industry with the highest wage, and the country will completely specialize. Perfect specialization is not observed in real-world data, so I impose that labor is sticky between industries. Feltenstein and Plassmann (2008) make a stronger assumption that labor is completely immobile between industries. I relax this requirement by using an exponential share function. Equation 7 shows how labor is distributed across industries based on wages.

$$L_{ni}^{s} = \frac{\exp(\varphi_{ni} w_{ni}^{r} + \Phi_{\mathrm{ni}})}{\sum_{j=1}^{N} \exp\left(\varphi_{nj} w_{j}^{r} + \Phi_{\mathrm{nj}}\right)} l_n \tag{7}$$

L_{ni}^{s} is the labor supplied by the household in region n to industry i. Labor supply for an industry is determined as a share of overall allocated labor, which is then multiplied by the aggregate labor supplied to the region, $\bar{L}_{n}^{s}$. The variable w_{ni}^{r} is the relative wage, which is the wage in industry i divided by the average wage in region n. The first parameter is the sector elasticity, φ_{ni}, and determines the change between industries in response to a change in relative wages. If the sector elasticity is set to zero, labor becomes completely immobile between industries. The second parameter Φ_{ni} is the share parameter and is calculated such that the base case equilibrium matches benchmark data.

1.2.c Trade Flows, Tariffs, and Rebates

One issue with using a non-Armington model is incorporating empirically observed features of trade markets such as cross-hauling, home bias, and no perfect specialization. Part of this is taken care of in the structure of the firm and household. Up to this point, I have closely matched the non-Armington model presented in Feltenstein and Plassmann (2008), which prevents complete specialization by restricting the labor market. One drawback of this model is that it does not generate trade flows. If I were to solve this model as is, I would know how much of a commodity each region produced and bought, but not how those buyers and sellers are matched. The two previous models, Balistreri et. al. (2018) and Feltenstein and Plassmann (2008), use regions' net trade positions, production minus consumption, as a measure of trade. This may understate tariffs, however, if regions engage in cross-hauling. To account for this, I predict trade flows using information on previous trade flows and principles from the gravity trade model literature.

I define a function $T(\cdot)$ that predicts trade flows given a vector of regions' supply and demand shares and a set of parameters.

$$\mathbf{F}^j = T\left(D^j, S^j, \mathbf{A}\left(\boldsymbol{\tau}^{j(bc)}; \theta^{1j}, \boldsymbol{\theta}^{2j}\right)\right) \tag{8}$$

This function outputs a trade matrix $\mathbf{F}^j$ that describes the trade flows between the regions for a good j. Each element F_{nz}^j in the matrix $\mathbf{F}^j$ is the share of world production that is sent from origin z to destination n. I give an example of a trade matrix for the goods manufacturing industry in appendix Table A.7. Each row is the destination of a good, and each column is the origin. Intraregional trade is on the diagonal, so this is a measure of home bias. This function has three inputs: shares of world demand $D^j(n)$, shares of world supply $S^j(n)$, and a matrix $\mathbf{A}$ which is calculated from the baseline parameters and border costs. The matrix $\mathbf{A}$ contains the predicted shares of consumption based on government border costs such as import tariffs or export subsidies, represented by $\boldsymbol{\tau}^{j(bc)}$. This matrix also uses a scalar parameter, θ^{1j}, and an NxN matrix of parameters $\boldsymbol{\theta}^{2j}$.

The function $T(\cdot)$ does not have a closed-form expression when N > 2, instead it uses row operations to calculate the trade matrix. However, below is an approximation of the trade flow prediction to better explain this portion of the model.

$$F_{nz}^{j} \approx \frac{a_{nz}^{j} D^{j}(n)}{\sum_{i=1}^{N} a_{ni}^{j} D^{j}(i)} S^{j}(z) \tag{9}$$

$$a_{nz}^{j} = \left[\frac{\exp\left(\left(1-\theta^{1j}\right)\ln\left(1+\tau_{nz}^{\mathrm{j(br)}}\right)+\theta_{nz}^{2j}\right)}{\sum_{i=1}^{N}\exp\left(\left(1-\theta^{1j}\right)\ln\left(1+\tau_{nz}^{\mathrm{j(br)}}\right)+\theta_{ni}^{2}\right)}\right]$$

Equation 9 would hold with equality if N=2, i.e., a bilateral model with two regions – home and foreign. The full algorithm that calculates $T(\cdot)$ for N>2 is used in the application and presented in chapter 2 section 2.3. Looking at equation 9, the importer's demand $D^{j}(n)$ and the supplier's production $S^{j}(z)$ are multiplied together as in the standard gravity equation. The variable a_{nz}^{j} is the effect of border (br) taxes such as import tariffs and export subsidies, which are denoted as $\tau_{nz}^{\mathrm{j(br)}}$. The effect of border costs depends on two parameters; the first is θ^{1j}, which is a trade elasticity parameter. The second parameter is θ_{nz}^{j}, which is calculated to match the equilibrium to the baseline data. This differs from the traditional Armington model by using relative quantities of production and consumption instead of relative prices.

This framework is comparable to the Eaton and Kortum (2002) model that combines a Ricardian model with a gravity equation. In that paper, the authors assume a continuum of heterogeneous goods made by firms with productivities determined by a Fréchet distribution. The model presented here is similar, except I do not make distribution assumptions about productivity. Instead, I assume representative firms create homogenous goods, factor availability and supply chain linkages determine comparative advantage, and then the gravity function determines trade flows. I compare my method of predicting trade flows to the traditional Armington model later in the paper after introducing and describing the dataset.

1.2.d Government

The government performs two functions, levying taxes and transferring income. For this paper, the government taxes CO_2 emissions and imports. Governments may also subsidize exports to other countries, which is given to the exporting firm. Taxes enter the model in the producer's problem through equation 1 and in the consumer's problem through equation 6 (the price index $\hat{P}_n$ includes taxes). I separate taxes into two parts, a carbon tax and a border cost.

$$\tau_n^j = \tau_n^{j(bc)} + \tau_n^{j(c)} \tag{10}$$

$$\tau_{nj}^{(bc)} = P^j \sum_{z=1}^{N} \frac{F_{nz}^j}{\sum_{i=1}^{N} F_{ni}^j} Tariff_{nz}^j \tag{11}$$

$$S_n^j = P^j \sum_{z=1}^{N} \frac{F_{zn}^j}{\sum_{i=1}^{N} F_{ni}^j} Rebate_{nz}^j \tag{12}$$

$$\tau_n^{j(c)} = cc_n^j \times Tax_{\$/CO_2} \tag{13}$$

Equation 10 is the total tax on a commodity in a region, which is the sum of tariffs and any applicable carbon taxes. Equation 11 calculates the tariff rate using the trade flows calculated earlier. The term $\frac{F^j_{nz}}{\sum_{i=1}^{N} F^j_{ni}}$ is the share of good j purchased in region n that comes from region z. I multiply this by the sum of the tariff rate n sets on goods from z, $Tariff^j_{nz}$. Trade flows are also partially determined by tariff rates, as shown in the previous section. This also assumes that the country is a price taker, sellers will not accept lower than the world price. So, the only affect a country has on the world price, P^j, is through its effect on world demand and supply. Since this is small compared to the size of the tariff, the home country bears the burden of the tariff. Similarly, the subsidy to firms in equations 3 and 4 is calculated in equation 12. The subsidy is calculated using trade flows and the rebate rate for goods exported from origin n to destination z, $Rebate^j_{nz}$. Again, the country is a price taker, so firms can only affect the world price through their effect on world supply. The means the exporting firm gets the full benefit of the rebate.

In equation 13, carbon taxes are calculated based on the content of carbon emissions released when a unit of fuel is consumed. The amount of carbon emissions released is calculated using a carbon coefficient cc^j_n, which is the amount of CO_2 released when a unit of good j is consumed. As this tax is levied when the fuel is burned, it allows the cost of carbon to be fully integrated into upstream prices through the supply chain. This also assumes that firms are not able to abate carbon at the intensive margin with technology such as scrubbers or carbon capture devices. I should also point out that this is considered production-based accounting of emissions in contrast to consumption-based accounting. While neither is the “correct” way to measure emissions, this production-based method gives the geographic source of the emission by tying it to where the fuel was burned. A consumption-based method would assign emissions based on where the final product was consumed.

1.2.e Equilibrium Solution

Equations 1-4 determine input demands for production, and equations 5-7 determine factor supplies and household consumption demands. Trade flows are calculated using equation 8, which determines transportation costs in equation 2 and border costs in equation 1 and equations 3 through 7. Equilibrium is defined as a point where these equations hold for all industries and households and where commodity and capital markets clear.

$$c_n^j + \sum_{i=1}^{J} X_{nj}^i = Q_n^j \quad \forall\, n \in \{1, \ldots, N\} \tag{14}$$

$$\sum_{n=1}^{N} c_n^j + \sum_{n=1}^{N} \sum_{i=1}^{J} X_{nj}^i = \sum_{n=1}^{N} Q_n^j \tag{15}$$

$$\sum_{n=1}^{N} \sum_{j=1}^{J} K_n^j = \sum_{n=1}^{N} \bar{K}_n \tag{16}$$

Equation 14 is the market-clearing condition for non-tradables, which must clear for each region, and equation 15 is the market-clearing condition for all other tradable commodities. In both equations, the left-hand side is the sum of consumer and intermediate demand for the commodity, and the right-hand side is total output. Equation 16 clears the capital market. The left-hand side is the global demand for capital input across all firms in all regions, which is determined by equations 1 and 4. The right-hand side is the sum across all household capital allocations.

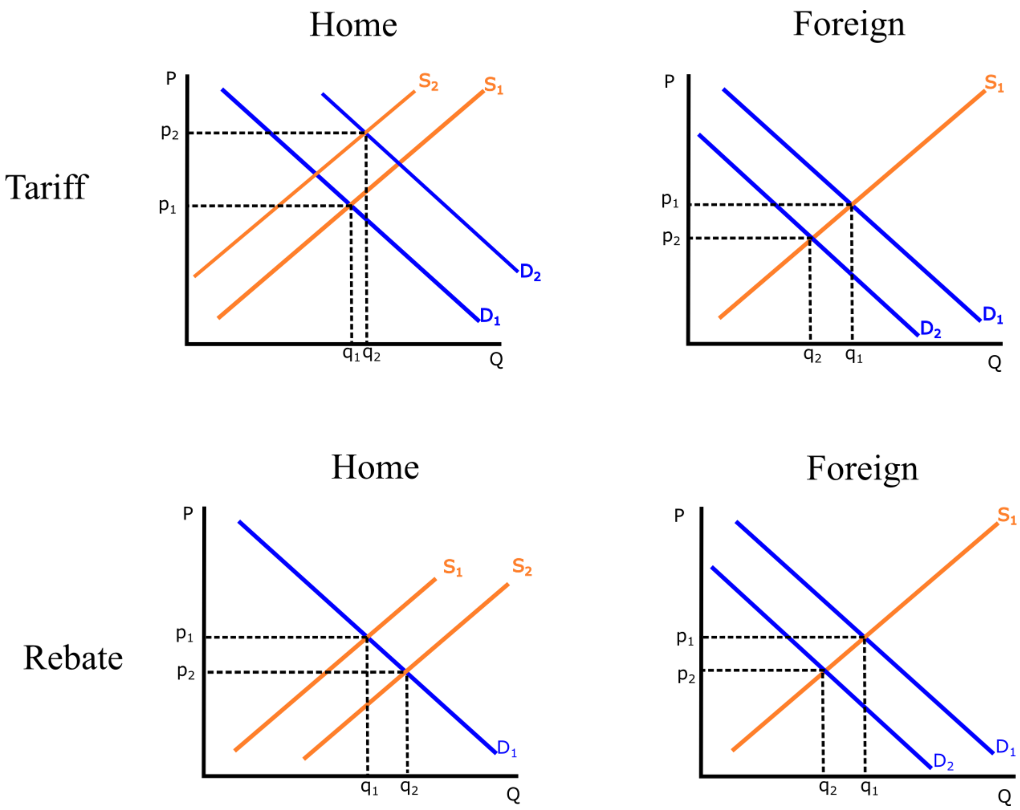
To conduct policy experiments, I first simulate a base case scenario, which is the equilibrium with no carbon policy. I then introduce the new policies, such as carbon taxes and BCAs, and simulate the counterfactual scenario. This counterfactual is compared to the base case to determine the impact of the policies. Equilibrium is found numerically using a simplex method based on Scarf's algorithm (Scarf and Hansen 1973). Due to the numerical calculation of trade flows, the equation for this may not be differentiable at all points; for example, it may have kinks or sharp turns. The simplex method I employ proves useful over Newton methods in that it can handle these types of non-differentiable equations.

1.2.f Differences Between Models

The most important difference between the non-Armington and Armington model, for the purposes of this paper, is how tariffs and rebates affect domestic prices. In an Armington model, tariffs and rebates both reduce carbon leakage, which is confirmed numerically by several studies mentioned previously. In the non-Armington model, a rebate may be able to reduce leakage, but a tariff likely will not.

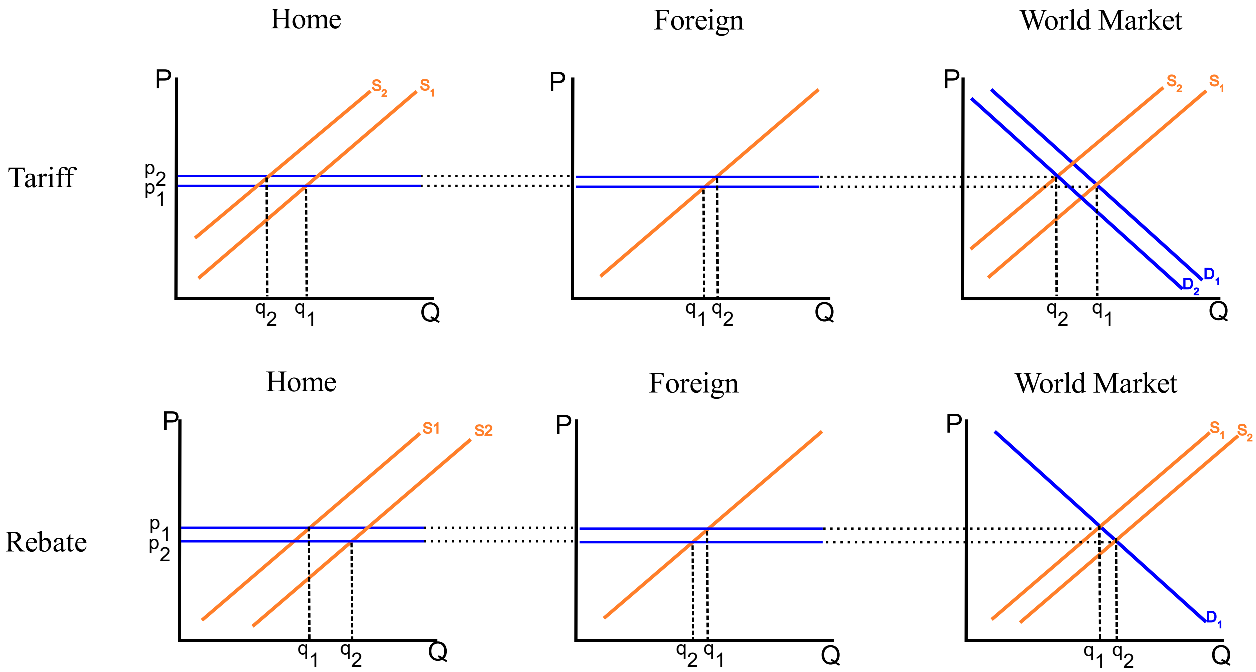
To simplify the analysis, consider an Armington model with two regions, home and foreign. Suppose that the home country has already imposed a carbon tax and is trying to control leakage through border controls. This means they need to increase the home firm's share of world production and decrease the share of the foreign firm. Figure 1.2 shows the effect of a tariff and rebate for an arbitrary polluting good in an Armington world. The left two panels show the market for goods produced by the home firm and the right column of panels show the market for goods produced by the foreign firm. Since these goods are differentiated by where they are produced, they face separate downward sloping demand curves. First, look at the top two panels, which show the impact of a carbon tariff. The home country imposes a tax on foreign produced goods, which shifts the demand curve for the foreign good inward. The price for the foreign good falls, and a movement along the supply curve leads to the foreign firm supplying less to the market.

Figure 1.2: Impact of a BCA in an Armington Model



Notes: These four graphs show the effect of a tariff and a rebate for an arbitrary polluting good under the Armington assumption. The left panels show the market for goods produced at home and the right panels show the market for goods produced in a foreign country. In the top panels, the home country imposes a tariff on foreign goods. The demand curve for foreign goods shifts inward, and the demand for home goods shifts out due to the substitution effect. The supply curve for the home country also shifts inward since the tariff is on the home country's inputs. The bottom two panels show the effect of a rebate to firms in the home country. The supply curve shifts out, and there is a movement along the demand curve. The new lower price causes consumers to substitute away from foreign goods, and the demand curve for foreign goods shifts inward.

Figure 1.3: Impact of a Tariff and Rebate in a Non-Armington Small Country Model



Notes: This figure shows results the impact of a tariff and rebate for an arbitrary polluting good. The right panels show the world supply and demand, the center panels show the foreign firm supply, and the left panels show the home firm supply. Since home and foreign are price takers, they face a perfectly horizontal demand curve equal to the world price. In the top panels a tariff shifts world demand and supply inward. However, only the home firm's inputs are taxed, so their supply curve shifts inward. In the bottom panels, a rebate shifts world supply out, lowering the world price, but only the home firm's supply curve shifts outward.

Through the substitution effect, the demand curve for the good produced at home shifts outward. Polluting goods often use other polluting goods as inputs in intermediate consumption, so the home firm's inputs are being taxed, and their supply curve shifts inward. This leads to a higher price for the home good and an ambiguous effect on the quantity supplied. However, it is very likely that the quantity reduction for the home firm is smaller than that of the foreign firm. This leads to the home country producing about the same amount and the foreign firm producing less. This brings back production to the home country, which reduces the amount of leakage from the carbon tax.

Similarly, one can consider a rebate to the home firm for carbon taxes paid on goods exported to the foreign country. In this case, the home firm receives a subsidy, which shifts their supply curve outward. This causes a movement along the demand curve for the good produced at home and a subsequent price decrease. This price decrease causes buyers of the foreign good to substitute toward the home good and shifts the foreign good demand curve inward. This causes a movement along the supply curve, which lowers the price for the foreign good and reduces the amount supplied. Thus, we have the same basic effect as the tariff; the home country produces more of the polluting good and the foreign country produces less. This brings production back under the coverage of the carbon tax and reduces leakage. A full BCA would be a combination of these two effects, which leads to a larger reduction in carbon leakage.

So, how does this analysis change under a non-Armington model? Consider the same setup, a bilateral model with a home and foreign firm. The big difference here is that the home and foreign firms are small and cannot influence the world market price very much. In the Armington model, we assume implicitly that both countries are "big" in the sense that they are the only ones who can produce their respective goods. Any change in their respective supplies will have strong effects on the market price of their output. In the non-Armington model, there is one world price which is determined by the interaction of world supply and demand. The home and foreign firms are price takers.

Figure 1.3 shows the effects of a carbon tariff and rebate for an arbitrary polluting good in a non-Armington world. In the rightmost column, the world market shows how the world price is determined. The left two columns are the market diagrams for the home and foreign firms. The home and foreign firms are price takers, so they face a perfectly horizontal demand curve equal to the world price. To see the effect of a tariff, first look at the world market diagram. Since there is a tax on consumption somewhere in the world, the demand curve shifts inward. The supply curve also shifts inward, since polluting firms use polluting goods as inputs, and taxes on these goods have increased. The quantity supplied falls and the world price stays roughly the same. The actual effect on price is ambiguous, but I have drawn the picture to end up with an increase in the world price, which corresponds to my results from the numerical simulation presented later. The foreign firm sees an increase in the world price and moves along the supply curve to produce a little bit more. The home firm also sees this increase in the world price, but their supply curve also shifts left due to the tariff on their inputs. The result is a decrease in production for the home country and an increase in production for the foreign country. This leads to *increased* carbon leakage since less of the world production of the polluting good is covered by home's carbon tax.

This is a stark difference from the Armington model. The primary reason for this difference is that the home country cannot separately influence the foreign firm's price. This point was first made in a seminal paper on optimal tariffs by Markusen (1975). Since both firms receive the same world price, the supply shift in the home country dominates and leakage increases. Since buyers do not have preferences over the origin of goods, the foreign firm does not have to lower their price to encourage other buyers to purchase their goods. If the home country will not buy the foreign good at the world price, somebody else will. This means that the burden of the tariff falls primarily on the home country and the export supply curve is perfectly elastic. Some trade economists may argue that this analysis might hold for small countries, but not for big countries like the US. However, recent empirical studies of US tariffs on Chinese imports show this is indeed the case. Import tariffs imposed by the US were not able to push down Chinese output prices, and the entirety of the tax incidence was borne by US buyers (Cavallo et. al. 2019, Amiti et. al. 2020, Fajgelbaum et. al. 2020, Flaaen et. al. 2020).

Finally, I also look at the effect of a carbon rebate in a non-Armington world in the bottom panels of Figure 1.3. Again, starting with the world market, the world supply curve shifts out due to the subsidy the home firm receives on its exports. This causes a movement along the world market demand curve and quantity supplied increases and the world price falls. The new lower price causes a movement along the foreign firm's supply curve, and they begin to produce less. The home firm also sees this price decrease, but they are receiving the subsidy, so their supply curve shifts out. This leads to more production in the home country, which is covered by a carbon tax. Thus, a rebate may be able to reduce leakage in a non-Armington model. A full BCA would likely include both policies, and the effect is some combination of the two competing forces. These simple diagrams show the intuition of the model, but to put numbers on these effects I now turn to numerical simulation.

1.3 Data and Calibration

I calibrate the model using data from the World Input-Output Database (WIOD), which includes environmental satellite accounts[1]. The WIOD contains data on 35 industries across 40 countries and creates a balanced world representative input-output matrix. I only need one year of data, so I use 2011, which is the most recent year available in the 2013 release. I aggregate the database to 15 industries and 5 regions, listed in Table 1.1. I combine the members of the European Union to create the Europe region, and I combine Canada and Mexico to form the

[1] Dataset may be downloaded from www.wiod.org.

North America region. China and the United States are each their own regions, and all other countries are combined into the "Rest of the World" region. The Rest of the World region accounts for about half of global emissions, whereas China, Europe, North America, and the United States account for the other half.

In the baseline data, fossil fuels are aggregated together in a single mining and resource extraction industry. I use the more detailed make-and-use tables from the WIOD database to split out fossil fuel extraction industries. This allows me to disaggregate coal, oil, and natural gas extraction from the mining industry. However, natural gas and crude oil are still aggregated in an "oil and gas" industry. I disaggregate this industry using energy use satellite accounts, which report detailed energy input use by region and industry. This leaves me with three fossil fuel industries: coal, crude oil, and natural gas.

The WIOD also produces data on emissions by fuel source, which allows me to assign emissions content to different fuel types in my model. Crude oil, however, is used first as an input to the petroleum refining industry, which produces usable liquid fuels such as gasoline, diesel, and jet fuel. The WIOD does not report any emissions for crude oil but instead shows emissions from these downstream refined products. Since the data is structured in this way, it makes more sense to tie emissions from petroleum to the use of refined petroleum products rather than crude oil. This gives three fuel sources for CO_2 emissions: coal, natural gas, and refined petroleum. More information on how I aggregated regions and disaggregated industries is discussed in Appendix A.

To calibrate the model, I need to set elasticity parameters in the production functions to match estimates from the literature. After setting the elasticity parameters, I assume prices in the initial equilibrium are equal to unity, and I solve for the remaining parameters such that the base case equilibrium is equal to data in the WIOD. The parameters needed for the model and corresponding values are listed in Table 1.2. All elasticity values come from the literature except the sector elasticity in equation 7 and the transportation elasticity in equation 2. Instead, I estimate both those elasticities using data from WIOD in the next section. The materials nest and intermediate nest elasticities are set at 0.97 and 0.88, respectively, which comes from Van der Werf (2008). The fuel nest has three papers with similar structures, so I take a central value across those studies and get a value of 1.07 (Xie and Hawkes 2015, Khalid and Jalil 2019; Smyth, Narayan, and Shi 2012). Consumption is assumed to be Cobb-Douglas, so parameters for the utility function are consumption shares reported in the WIOD. To calibrate the labor-leisure choice in equation 6, I match the Frisch elasticity of labor supply to estimates from the literature. This is an elasticity commonly estimated, which I set at 0.5 based on a survey of estimates from Chetty et. al. (2011). Two sets of parameters go into equation 8, which predicts trade flows. The first parameter θ^{1j} is a trade cost elasticity. The estimate of this parameter comes from Hertel et. al. (2007), which estimates trade elasticities using border costs such as tariffs. These elasticities are presented in appendix Table A.5. The second parameter in the trade equation is $\boldsymbol{\theta}^{2j}$, which is a matrix of parameters calibrated so that trade flows in the baseline equilibrium match those in the WIOD.

Table 1.2: Parameter Values and Sources

	Parameters	Value	Source
Production:			
Fossil fuel elasticity	σ_{ff}	1.07	Xie and Hawkes, 2015; Khalid and Jalil, 2019; Smyth, Narayan, and Shi, 2012
Fossil fuel scale and share	$\alpha_{coal}, \alpha_{ngas}, \alpha_{oil}, \gamma$	*	Calibrated from WIOD
Intermediate elasticity	σ_{int}	0.88	Van der Werf, 2008
Intermediate scale and share	$\alpha_{ff}, \alpha_n, \gamma_{int}$	*	WIOD
Materials elasticity	σ_{mat}	0.97	Van der Werf, 2008
Materials scale and share	$\alpha_{ff}, \alpha_n, \gamma_{int}$	*	WIOD
Final product scale and share	ω, γ_{prod}	*	WIOD
Household:			
Sector elasticity	φ	1.22	Estimated in paper from WIOD
Sector constant	Φ	*	WIOD
Consumption shares	ψ	*	Income shares from WIOD
Labor elasticity	ν	0.5	Chetty et. al. (2011)
Trade:			
Trade elasticity	θ^1	**	Hertel et. al. (2007)
Trade constant	θ^2	*	Calibrated from WIOD
Transportation elasticity	η	0.17	Estimated in paper
Emissions:			
Carbon coefficient	cc	***	Calibrated from WIOD

Notes: This table shows all parameter value choices and sources. An entry of "varies" indicates that the value varies over industry and region, making it unrealistic to report here. Values taken from the literature are presented and the sources of those values in the literature are also indicated.

* These parameters are calculated for each industry and region, so there are too many to express here. I detail how the data from the WIOD is used with the chosen elasticity values to calibrate the model in appendix A.

** Table A.5 in appendix shows trade elasticities used for each industry.

*** Table A.6 in appendix shows carbon coefficients for all regions and fuel types.

1.3.a Estimation of Transportation and Sector Elasticities

I parameterize equation 2 by using regression analysis. The transportation elasticity in equation 2 is the elasticity between distance and transportation cost. This can be estimated in my data using the following regression equation:

$$\ln\left(s_{nt}^{j}\right) = \beta_1 \ln\left(d_{nt}^{j}\right) + \boldsymbol{\beta}_{2n} + \boldsymbol{\beta}_{3j} + \epsilon_{nt}^{j} \tag{17}$$

$$d_{nt}^{j} = \sum_{z=1}^{N} D_{zn} \times F_{zn}^{j}$$

The outcome variable in equation 17 is the share of international trade costs in the transportation composite. The WIOD contains information on international trade costs for each industry for the years 1995 through 2011. I divide this by the total amount spent on transportation services to generate s_{nt}^{j}. The explanatory variable in equation 17 is the average distance traveled by a unit of output. This is calculated the same way as in equation 2. The trade flows F_{zn}^{j} come from the WIOD and distance between countries, D_{zn}, is calculated using the geosphere[2] package from the statistical language R. The last two coefficients, $\boldsymbol{\beta}_{2n}$ and $\boldsymbol{\beta}_{3j}$, are vectors of region and commodity fixed effects, respectively.

The regression results are presented in Table 1.3. The coefficient of interest is in the top row. The columns differ by which fixed effects are included, but all specifications give the expected sign and are statistically significant. The elasticity estimates are between the range of 0.17 and 0.55, which is close to a previous estimate of this elasticity, 0.26 (Novy 2013). I use the lowest estimate with both region and commodity fixed effects, 0.17, as my baseline specification, but I investigate the full range of estimated elasticities in my robustness checks.

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[2] The R programming language has a repository available at www.cran.r-project.org, which can be accessed to obtain the geosphere package. Distance is measured as the miles between the center of two countries.

Table 1.3: Regression Results for Transportation Elasticity

Coefficient	$\log(s_n^j)$			
β_1	0.52*** (0.0363)	0.56*** (0.0388)	0.26*** (0.0344)	0.17*** (0.0407)
Region FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
R^2	0.136	0.166	0.675	0.726

Obs. = 1,296; *** = significance at the <1% level; standard errors in parentheses

Notes: These are the estimates for the coefficients in equation 13. The explanatory variable is the average distance a good is shipped, and the dependent variable is international trade costs. The top row is the elasticity between distance and trade costs. Region and industry FE indicate whether fixed effects were included in the regression.

I also estimate the sector elasticity, which determines how labor is distributed across industries based on wages since this is not commonly reported in labor economics. To do this, I use income accounts from WIOD to construct a database of hourly earnings and employment shares by industry[3]. However, a simple regression between earnings and employment indicates a negative relationship. This is would indicate that workers move to industries with *lower* relative wages. This is because I only observe equilibrium outcomes, which is determined by both supply and demand curves. So, OLS will not be able to estimate the effect of relative wages on labor supply. This is due to the engogeneity of prices and quantities being simultaneously determined in a market (Manski 1993). To identify the supply curve, I use a simultaneous equations model (SEM). The structure of the equations in the model is:

$$Supply\colon \log(employment_{ir}) = b_{10} + b_{11}\log(wage_{ir}) + \epsilon_1$$

$$Demand\colon \log(employment_{ir}) = b_{20} + b_{21}\log(wage_{ir}) + BX + \epsilon_2$$

[3] This uses the supplemental files of Socio Economic Accounts

Where $employment_{ir}$ and $wage_{ir}$ are the employment shares and wages of industry i in region r. These two variables are the same in both equations, which reflects the simultaneous nature of the market price and quantity. The first equation is the labor supply curve, and the second is labor demand curve. The second equation includes a vector of indices for capital inputs, intermediate inputs, value-added inputs, and the quantity of output. Identification in SEM requires that there is at least one variable in the demand equation that does not appear in the supply equation (Wooldridge 2010). The vector of indices in the second equation affects the demand for labor, but I assume that they do not affect labor supply. This allows me to use this vector of demand-side variables as a valid instrument for wage in the labor supply equation.

I estimate this model using two-stage least squares (2SLS) and present the results from the second stage in Table 1.4. I show four specifications, increasing the number of instruments for each column from left to right. In the full specification, I use all four instruments, which means the system is over-identified. I get the lowest estimate when including all demand-side shifters as instruments. This estimate also has the best first stage fit, so I use 1.22 as my baseline estimate for the sector elasticity. This indicates that a 10% increase in the industry wage leads to a 12% increase in the share of labor supplied to that industry.

Table 1.4: Regression Results for Sector Elasticity

	log ($employment$)			
log ($wage$)	1.95***	1.35***	1.36***	1.22***
	(0.171)	(.087)	(0.092)	(0.075)
Instruments:				
Value-Added	Yes	Yes	Yes	Yes
Intermediate	No	Yes	Yes	Yes
Output	No	No	Yes	Yes
Capital	No	No	No	Yes

Obs. = 6,929; *** = significance at the <1% level; standard errors in parentheses

Notes: These are the results from a two-stage least squares estimate of a simultaneous equations model. The first stage regresses wages on a subset of the four supply side instruments. The second stage, presented here, estimates the labor supply response to a wage change.

1.4 Results from Policy Simulations

The first scenario I consider is a carbon tax on three fuels: coal, natural gas, and refined petroleum[4]. This fee is a per-unit tax on fuel, defined in equation 13, that is charged based on the tons of carbon dioxide that are emitted upon consuming (i.e., burning) the fuel. I simulate a $50 tax per ton of CO_2 in the US. I then consider three types of border adjustment policies: a tariff only, an export rebate only, and a full BCA which includes both a tariff and an export rebate. Which goods to apply the tariffs and rebates to is an open question fraught with debate. However, the consensus seems to be carbon intensive and trade exposed (CITE) goods. I choose four industries that match these criteria: mining, goods manufacturing, chemicals manufacturing, and other manufacturing. Tariff and rebate rates are determined using data on emissions intensity by region and industry. Tariffs are calculated such that the price of the good is increased by how

[4] In emission satellite accounts from the WIOD, very few emissions result from refining crude petroleum, rather most of the emissions occur when the refined petroleum is consumed (burned). For this reason, using refined petroleum rather than crude oil gives a better match to global emissions.

much the foreign country would have spent on a carbon tax given their technology and emissions intensity. The rebate is based on how much home firms spend on the carbon tax for inputs.

I present the impacts from these policies on emissions in Table 1.5. The first column presents the results from a $50 carbon tax in the US without any border adjustments. The first row shows the total abatement by the US, which was 3.8% of world emissions. The second row is the leakage in emissions outside the US, 1.1% of world emissions. Adding these two rows gives the net world abatement of 2.7%. Dividing the leakage by gross abatement calculates the leakage rate, which can be compared to previous studies. My non-Armington model calculates a leakage rate of almost 30%, which is more than twice as high as the 12% average leakage rate reported by the EMF survey of CGE models (Böhringer et. al. 2012). The only other paper that explores the effect of the Armington model finds similar results. Balistreri et al. find that leakage rates are 15.7% using the Armington model and 26.5% using a non-Armington model.

These results are both expected and puzzling. On the one hand, carbon leakage would likely be higher in a non-Armington model due to highly elastic export supply curves. On the other hand, there is little empirical evidence of carbon leakage. The European Union Emissions Trading Scheme (ETS) had no effect on imports of cement and steel (Branger, Quirion, and Chevallier 2016), and, despite increasing environmental stringency, the US has not experienced carbon leakage in its manufacturing sectors (Brunel and Levinson 2021). This is puzzling since the previous trade literature has suggested that the Armington assumption generates changes in trade volumes that are too small (discussed in chapter 2). However, the carbon leakage literature suggests it generates changes that are too big. This could be due to my model not including enough frictions in the international capital market, which would limit offshoring of production.

Specifying a model of offshoring and international capital movements is beyond the scope of this paper, but this puzzle is an interesting avenue for future research.

Table 1.5: Summary of Impact from \$50/ton CO2 Carbon Tax in United States

		Border Adjustment Policies		
	Carbon Tax	Tariff	Rebate	BCA
Emissions:				
Gross Abatement	-3.81%	-3.83%	-3.76%	-3.79%
+				
Leakage	1.13%	1.20%	0.94%	1.03%
=				
Net Abatement	-2.68%	-2.63%	-2.82%	-2.76%
Leakage Rate	29.6%	31.4%	25.1%	27.1%
Economic Variables:				
Aggregate Labor	-0.63%	-0.69%	-0.58%	-0.64%
Aggregate Wage	-1.67%	-1.83%	-1.47%	-1.64%
Real GDP	-0.62%	-0.66%	-0.59%	-0.62%

Notes: This table shows carbon leakage under different carbon price policies. The first four rows show data on emissions and leakage. The first row is the gross abatement as a percent of world emissions by the United States. The second row shows the amount of leakage as a percent of world emissions, and the third row is the summation of row 1 and 2. The leakage rate is simply the negative of the second row divided by the first. Economic variables are expressed as percent changes from the baseline business-as-usual scenario.

Returning to the results in Table 1.5, columns two through four show leakage and economic impacts when including different border adjustment policies. The second column is the impact of a carbon tax with a tariff on carbon intensive inputs. As predicted in section 1.2.g, the tariff alone does not decrease carbon leakage. The supply shock in the home country dominates and carbon leakage increases to 31.4%. The US also sees more detrimental outcomes in economic variables. Compared to the scenario with only a carbon tax, aggregate labor supply falls by 0.06 percentage points more, the aggregate wage falls by 0.15 percentage points more, and real GDP falls by 0.04 percentage points more.

Under a rebate only border adjustment, I do find leakage decreases to 25.1%, which is a 15% reduction in leakage. Gross abatement (abatement by the US) is smaller than in the carbon tax only scenario. This is because the rebate increases US production of polluting goods to bring more production under the coverage of the carbon tax. However, leakage falls enough such that net abatement is higher. Economic conditions are also better under this policy, which is partly due to production being brought back to the US and partly due to the burden of the carbon tax being smaller, since the government is subsidizing polluting firms. Compared to scenario with only a carbon tax, aggregate labor supply is 0.06 percentage points higher, the aggregate wage is 0.2 percentage points higher, and real GDP is 0.03 percentage points higher.

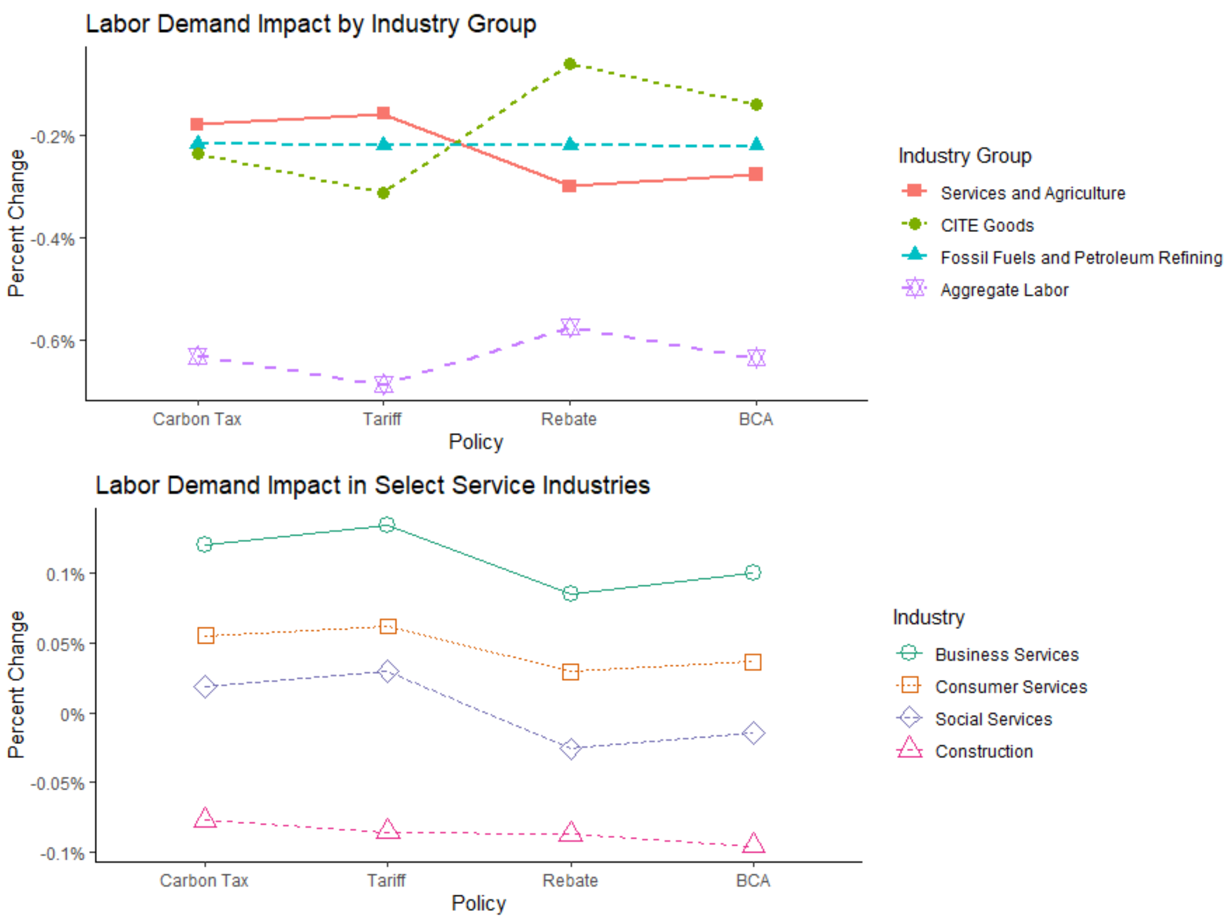
The full BCA policy is a tariff and rebate combined. The results are presented in the final column of Table 1.5. Carbon leakage decreases to 27.1%, which is an 8.6% reduction from the carbon tax only scenario. This number is a far cry from traditional Armington models that predict BCAs can reduce carbon leakage by about 30%. This difference is driven mainly by the fact that the tariff effect in this model increases carbon leakage, so the rebate is competing with the tariff. Economic outcomes are surprisingly similar to the carbon tax only scenario. Aggregate labor supply is slightly lower, the aggregate wage is slightly higher, and there is no discernable effect on GDP.

So, while a BCA policy does seem to reduce leakage without much harm to the economy, the predicted reduction is much smaller in this model. While the effect from the rebate can help reduce leakage by encouraging more production in the taxed region, the tariff effect works against the rebate. A rebate only policy may be preferable for leakage concerns, however it can be costly. A full BCA policy pays for itself in government revenue. In my simulation a carbon tariff raises about $19 billion in revenue and the rebate costs about $15 billion, which is a net gain to the US treasury. Revenues from the carbon tax are $170 billion, so a rebate only policy would reduce carbon tax revenue by 9%. The question for policymakers is whether this revenue loss is worth the 15% reduction in leakage rates.

Aggregate labor market effects can be decomposed by industry as well, since carbon taxes disproportionately affect fossil fuel and manufacturing industries. Figure 1.4 shows two graphs breaking down labor market effects by industry. The top graph shows how the aggregate labor supply loss is distributed across industries. Under a carbon tax without border protections, CITE industries have the largest employment losses followed by fossil fuel industries and then service industries. Since CITE industries have very high exposure to the carbon tax, workers leave those industries and enter service industries which are relatively insulated from the tax. Including a tariff without a rebate leads to an even higher transfer of workers from CITE industries to services, again due to the supply shock for these firms.

Interestingly, including a rebate switches this pattern. Services become the biggest losers, and CITE industries have a much smaller labor decline. While a full BCA may not increase aggregate employment very much, it does seem to redistribute the burden of the tax on labor to the service sector. The bottom panel of Figure 1.4 shows how labor losses are distributed within the service sectors (transportation and agriculture are excluded). A tariff gives a small employment increase to business, consumer, and social services. These industries hold large shares of the aggregate labor supply and, thus, they pull in workers fleeing the CITE industries due to the tariff. A rebate for CITE industries means fewer workers leave those industries, so they see larger decreases in employment under a rebate policy. Construction, however, has a small share of the overall labor supply and is more exposed to the carbon tax since they often use emission intensive inputs. A tariff ends up causing a small decrease in construction employment. Again, a rebate causes more workers to stay in the CITE industries, so construction is not able to hire workers leaving those industries.

Figure 1.4: Labor Market Impacts from a \$50/ton CO2 Carbon Tax in United States

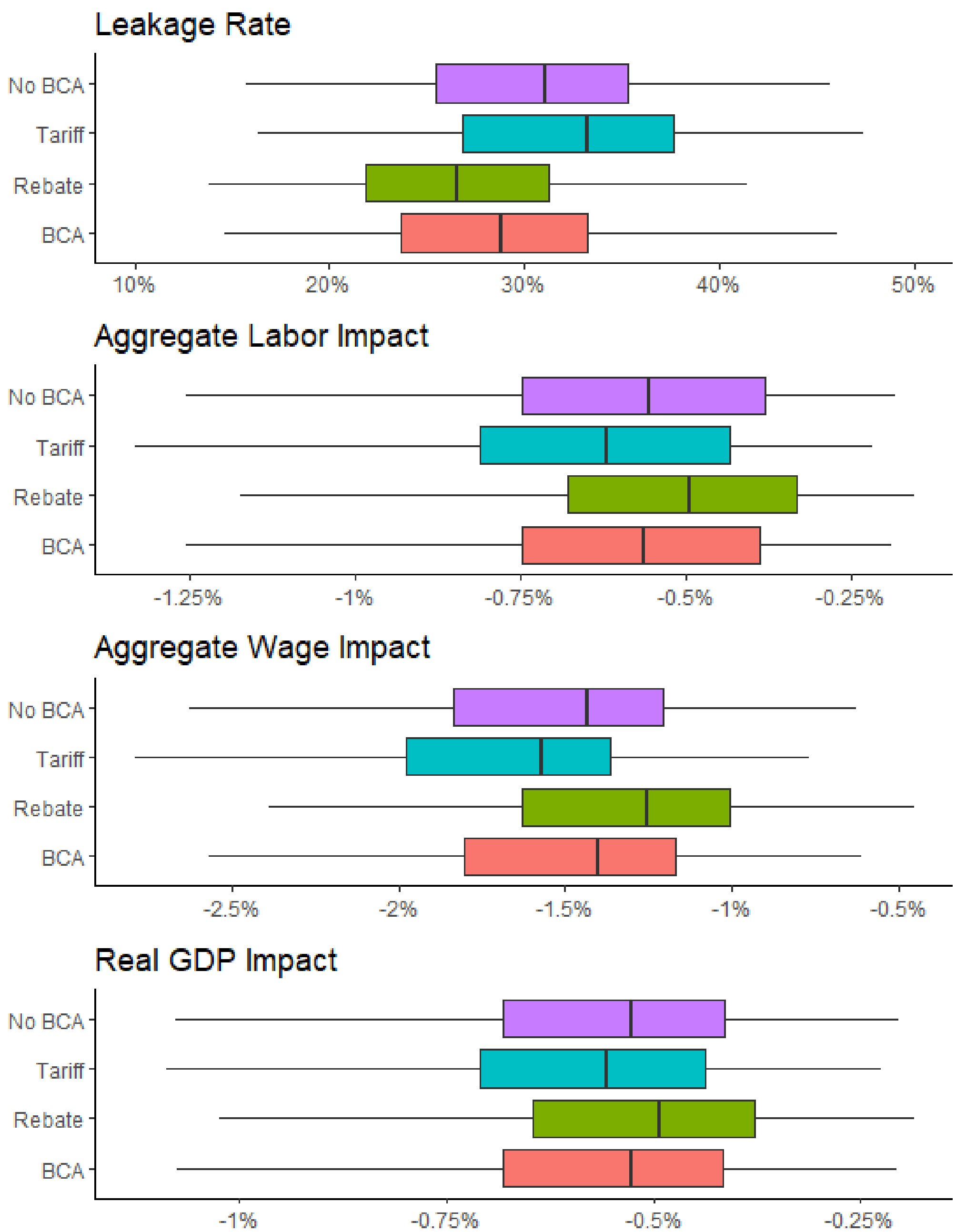


Notes: This figure shows employment impacts of four different policies. From left to right: a carbon tax without border protections, a carbon tax with a tariff on carbon intensive trade exposed (CITE) goods, a carbon tax with an output rebate for CITE industries, and carbon tax with a border carbon adjustment which includes both the tariff and the rebate. The top graph shows employment effects for three large sectors of the economy and the aggregate labor supply. The impacts are expressed in percent change of total labor supply so that the sum of the three sectors equals the aggregate labor effect. The bottom graph performs the same exercise, but selects four sub-sectors from the Services and Agriculture industry in the top graph.

1.4.a Monte Carlo Simulation

In the baseline simulation, I assume that all elasticities are the same across regions. This was because I take these estimates from the literature, and I could not find consistent estimates of these elasticities for all regions in my dataset. To check how my results respond to different parameterizations, I perform a Monte Carlo simulation of a $50 per ton of CO_2 carbon tax in the US with and without a BCA policy. For each elasticity parameter, I randomly select a value from a uniform distribution from a range around the baseline parameter. I randomly draw each of the three production elasticities: materials, intermediate, and fossil fuels, as well as the leisure elasticity and the sector elasticity. I also randomly draw values for carbon coefficients, which determine the amount of carbon released by different fuels. These were calculated for each region, and the difference of these numbers between regions may be important for carbon leakage if production moves to a region with more emission intensive technology. The ranges of these values I either take from the range of elasticities seen in the literature, or a range that I have estimated. More details on the process and ranges chosen are in Appendix B. Parameters are randomized among both region and industry, so this process allows for heterogeneity along both of those dimensions as well. After drawing a random set of elasticity parameters, the other parameters in the model are recalibrated to match the baseline data under the new specification. I then simulate a $50 per ton carbon tax with and without a BCA under the new calibration.

Figure 1.5: Results from Monte Carlo Simulations



Notes: These graphs are created from 100 simulations of a $50 per ton carbon tax under four different policies. Each graph shows the effect of each policy listed on the vertical axis. From top to bottom the policies are: a carbon tax without border protections, a carbon tax with a tariff on carbon intensive trade exposed (CITE) goods, a carbon tax with an output rebate for CITE industries, and carbon tax with a border carbon adjustment which includes both the tariff and the rebate.

The results discussed up to this point still hold under this exercise. The results from 100 simulations are presented in Figure 1.5. Box plots are presented to show the range of outcomes from the simulations. As expected, a tariff only policy on average predicts a 2.5 percentage point higher leakage rate compared to a carbon tax alone. This is slightly higher than the baseline simulation which predicted tariffs increased the leakage rate by 1.8 percentage points. The highest increase in leakage rates across all simulations was 19%. In no simulation did a carbon tariff reduce leakage compared to the carbon tax only policy. A rebate only policy is predicted to lower leakage rates by 5.7 percentage points on average, which is an 18% leakage reduction. The largest leakage reduction across all simulations was 37%. Finally, a full BCA policy reduces leakage by 2.9 percentage points on average, which is an 8.5% reduction. The largest reduction in leakage from a BCA policy across all simulations was 15%.

Results on economic variables show the same pattern as well. Aggregate labor supply decreased by and average of 0.05 percentage points more under a tariff only policy compared to a carbon tax without border protections. This goes in the other direction for a rebate. Aggregate labor supply is 0.05 percentage points higher on average when a rebate only policy is added to a carbon tax. Aggregate wage declines were 0.15 percentage points higher on average when adding a tariff and 0.2 percentage points lower when adding a rebate. Real GDP declines were 0.04 percentage points larger on average when adding a tariff and 0.04 percentage points lower when only adding a rebate. For all these variables, a BCA causes the tariff and rebate effects to cancel out, and the effects of a BCA are not discernably different from the carbon tax without border protections.

While this exercise shows that there can be considerable heterogeneity in the magnitudes of the outcomes of these policies, the broad conclusions of this paper still hold. Carbon tariffs increase leakage, and export rebates decrease leakage. Additionally, reductions from border carbon adjustments seem to be smaller than what has been reported by other studies. The largest leakage reduction from a BCA I find is 15%, which is still only half the 30% average rate predicted by previous Armington models.

1.5 Conclusion

International trade is a powerful force and important to consider when analyzing national tax policies. CGE modeling is often employed when determining how public policy will affect international trade. These models depend on the Armington assumption, which differentiates goods by the origin of production. In this paper, I build a CGE model that does not rely on the Armington assumption. This model differs from previous non-Armington CGE climate models, in that I introduce a method for predicting trade flows. I find that carbon leakage rates are higher using a non-Armington model. I find similar leakage rates to the only other non-Armington study of carbon leakage, despite different datasets and largely different model structures. However, I also find that if half of global emissions are covered, leakage rates drop to 16%.

The second result is that the typically suggested remedy, a BCA, is not as effective in reducing leakage in a non-Armington framework. In this non-Armington framework, firms in all regions face the same market demand curve. So, tariffs can redistribute trade flows, but they cannot reduce the production of carbon intensive goods in untaxed regions without reducing it in the taxed region as well. Many of the industries covered by carbon tariffs are inputs for domestic production, which means the home country experiences a supply shock. This causes production in the taxed region to fall and production in the untaxed region to expand, leading to higher carbon leakage rates under a carbon tariff. This finding is robust to several parameterizations. I also find that tariffs lead to contractions in aggregate labor supply and GDP and a fall in the aggregate wage.

When lawmakers are designing BCAs, it is crucial that they include an export rebate for it to have any effect. Even then, the effects may be small. One possible avenue for future research is determining how much effect a country can have on foreign output prices. If a country has enough influence on the world price, it may be possible for tariffs to reduce leakage. However, as globalization increases and countries begin trading more in intermediate goods, the role of the Armington assumption seems to be diminishing. Policymakers should be wary of this when enacting trade policy.

Chapter 2: Non-Armington Application to NAFTA

2.1 Introduction

Governments have long held considerable influence over trade with the outside world, an observation made by Adam Smith back in 1776. Since Smith's time, international trade has increased dramatically, relative to output, trade tripled during the last half of the 20th Century. However, it also the nature of trade that has changed, during that same time trade in manufacturing goods grew 50% faster than total trade (Hummels 2007). As supply chains become more integrated, many governments have pursued more open trade policies by entering into free trade agreements. When analyzing the effects of trade policies, modelers often use the Armington assumption. While this model is useful for incorporating important features of international trade, it has some weaknesses in policy analysis.

In the first chapter, I discussed how the Armington assumption changes environmental trade policy outcomes. Two other issues arise with the Armington assumption. The first is that it predicts small changes in trade in response to changes in trade policy. This problem arises because parameterizing the Armington model for industries with little to no previous trade leads to predictions of trade volumes being "stuck on zero" (Kuiper and van Tongeren 2006). In other words, it is difficult to induce large changes in trade in policy applications. Secondly, the Armington assumption can give a large upward bias in optimal tariff calculations in comparison to homogeneous trade models. In response to some scenarios, the Armington assumption can generate optimal tariff rates over 100% (He, Li, Wang, and Whalley 2017).

While this paper focuses on the first problem, the second problem is related to the issue brought up in chapter 1, if the country has little pricing power, then a tariff may not achieve the goals of the policymaker. However, in the past half century, many countries have pursued more open trade policies, often forming free trade areas without any tariffs on trade. One notable example is the North American Free Trade Agreement (NAFTA). While most research agrees that this policy had overall positive welfare effects, the changes for individual industries were much larger than predicted by CGE models of the time (Caliendo and Parro 2015). Some have argued that this occurs because the Armington functional form does not effectively capture the introduction of new products in trade (Zhai 2008). Others argue that adding preferences on the export side may improve prediction of the Armington model (de Melo and Robinson 1989). There are also models that adjust the Armington parameters to amplify trade changes in industries with little trade (Kehoe, Rossbach, and Ruhl 2015).

One paper, Kehoe (2005), shows the problem of small changes directly by comparing CGE predicted effects of the North American Free Trade Agreement (NAFTA) against observed data. Kehoe concludes that these CGE models were unable to generate the large changes that were seen in data. He further suggests that a non-Armington model may be able to generate those large changes. In this paper, I investigate this claim using a trade model that does not appeal to the Armington assumption. Instead, I model each industry as producing a commodity that is homogeneous across borders. I then go through an application of counterfactual analysis using this model. I compare my results to the data in a fashion similar to Kehoe to show when the non-Armington model may be useful to researchers.

Several papers have used CGE models to analyze free trade agreements. The model Kehoe focuses on is the Brown-Deardorff-Stern CGE model (Brown, Deardorff, and Stern 1992). This model uses a combination of the traditional Armington model and another model of imperfect competition derived from Krugman (1979). Other authors have used a Ricardian model derived from Eaton and Kortum (2002) to analyze the effects of NAFTA (Caliendo and

Parro 2015, Shikher 2012). These Ricardian models find larger trade impacts than Armington models, however they require modelers to impose a distribution of productivity across countries for each industry. In this paper, I do not impose any distributional productivity assumptions, which allows me to use standard input-output data that is a frequent resource used to calibrate CGE models.

The goal of this paper is to show how desirable features of the Armington model can be replicated in a non-Armington model. I then present a case study by applying this model to NAFTA and comparing my results to previous CGE models. To do this I begin with a non-Armington CGE model from Feltenstein and Plassmann (2008), which allows goods to be homogeneous by origin by imposing that labor is immobile between industries and regions. I extend this model by allowing for imperfect mobility across sectors and including a new algorithm that predicts trade flows. I contribute to the literature in two ways. The first is providing an analysis of the effects of NAFTA using a CGE model where goods are homogeneous by origin. The second is providing a tractable solution for estimating trade flows in a homogeneous goods model.

This paper also helps improve our understanding of modern trade behavior. As trade volume increases and costs fall, the intuition of the Armington assumption may be weakening as well. Many final products have large international supply chains, so consumers may not even know where their product was produced. Additionally, intermediate inputs are now a large and still growing share of international trade, and firms can produce those inputs practically anywhere they have the infrastructure and labor available. By modeling trade without the Armington assumption, governments can better anticipate how policy will affect each sector in the economy.

2.2 CGE Models and the Armington Assumption

Modelers formalize the Armington assumption by using aggregation functions that allow imperfect substitution between products of different origin. An aggregation function is simply a combination of two goods to form a single composite good. Typically, this function combines the domestic and foreign produced goods into a final composite good that is then used as final and intermediate consumption. The specification from Armington (1969) uses a constant elasticity of substitution form. This allows the modeler to estimate a substitution elasticity that can be taken directly to CGE models. Armington's 1969 paper was primarily econometric and focused on devising the algebraic underpinnings of estimating these trade elasticities.

The Armington model was a useful innovation since it could generate equilibria where countries did not perfectly specialize. Recall that Ricardo's model of comparative advantage was entirely frictionless and resulted in each country producing the good it could make at the lowest opportunity cost. Since each region produces only one good, this implies trade will result in a corner solution, i.e., perfect specialization. This innovation helped economists to estimate the possible welfare improvements from international markets, but corner solutions are non-existent in the real world. By adding frictions in the commodity market, one can stay away from corner solutions. Using the Armington model, each country *cannot* specialize since they can only make the type of goods they produce (England could not specialize in French cloth, only English cloth).

In this model, I use a framework that imposes frictions on the labor market to prevent perfect specialization. This can be done by imposing region specific labor supplies, so labor is not perfectly mobile across sectors and regions (Feltenstein and Plassmann). I restrict labor to be perfectly immobile between regions and sticky between industries. To have the model stay away from corner solutions, one needs to impose frictions in either the commodity markets or factor markets. While the Armington model puts this friction in the commodity market, in the non-Armington model, this friction is in the factor markets. This model is the same as the model used in Chapter 1, however the structure of production is much simpler. Instead of having 4 nests of production, I only use two in this paper.

Another important feature of the Armington model is the ability to model cross-hauling or two-way trade. This means that a country can import and export the same product category. Suppose the modeler restricts factors to allow imperfect specialization so several countries produce the same good. If foreign goods are perfectly substitutable for domestic goods, any positive transport cost would mean that optimizing agents only buy foreign goods if they cannot produce those goods themselves. In other words, even with imperfect specialization, perfect substitution implies countries are either exporters or importers, but not both. The Armington assumption allows for differentiation, which, in turn, allows countries to import and export the "same" good. While imports and exports may be in the same product category, they are produced in different countries, so they are treated as different products in the Armington model.

In this model, I extend current non-Armington models to include cross-hauling. While an Armington model uses the distribution of output prices to determine trade flows, the model I specify only creates a single world price for each commodity. Since there are no price differentials between countries, I instead use quantity differentials to predict trade flows. Each firm in each region sees the global price for their output and the domestic prices for inputs. Using this information, each region determines optimal output and consumption. Given the amounts that each region supplies and demands, I determine trade between regions using an algorithm that predicts trade flows based on historical trade flows and tariff rates. This method makes use of the observation from the gravity literature that trade patterns tend to be related to economic size and distance between countries. Countries that are bigger and closer together tend to be stronger trade partners.

This framework provides benefits from a modeling standpoint as well. The model can be calibrated with minimal data requirements. Trade elasticities are not needed to describe trade. In this model, I will include trade elasticities to determine the response to explicit trade costs – tariffs, however this is not necessary if trade costs do not change in the counterfactual. Estimating Armington elasticities often requires timeseries data on prices and trade volumes, which may not be available for some regions. Additionally, I do not need to estimate the distribution of productivity across firms. I assume a representative firm in each industry, which is a common assumption in CGE Armington models. This allows me to use widely available social accounting matrices (SAMs) from a single baseline year to calibrate the model.

2.3 Model Description

The model description is organized into 4 parts: production, consumption, trade flows, and government. In the model, there are J goods produced, bought, and sold by each of the N regions. Production is undertaken by a representative firm in industry in each region. Each region also has a representative household that supplies labor and capital to for firms to use in production. I assume that capital is internationally mobile, but labor is not. Labor is only supplied to the domestic market, and it is imperfectly mobile between industries.

Goods are homogeneous by origin, so each good has a single world price. All firms receive the world price for their output; however, importers may pay a higher price due to the presence of tariffs. Firms use the set of world prices and the price of capital to determine the optimal wage for workers in their industry and region. Workers then use posted wages to choose which industries to supply labor to. Using the distribution of labor supply and wages, I determine total production and consumption for each region. Then, using the production and consumption quantities for each region, I use an algorithm that builds a trade matrix based on baseline trade flows and tariffs. The equilibrium allocation is found by iterating on the vector of world commodity prices and the world price of capital until all goods and factor markets clear.

2.3.a Production

I use a neoclassical production function to describe production. Each firm combines capital, labor, and intermediate goods to create a unit of final output. I specify a Cobb-Douglas production function as follows:

$$Q_{jr}^{s} = F_{jr}\left(K_{jr}, L_{jr}, M_{jr}\right) = \gamma_{jr} K_{jr}^{a_{jr}} L_{jr}^{b_{jr}} M_{jr}^{c_{jr}} \tag{1}$$

$$M_{jr} = \gamma_{jr}^{\frac{\sigma}{\sigma-1}} \left(\sum_{i=1}^{J} \left(\rho_{jr}^{i} x_{jr}^{i}\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

K_{jr}, L_{jr}, and M_{jr} are capital input, labor input, and an intermediate composite input, respectively, for the firm that produces good j in region r. Each firm's intermediate composite is a combination of the J input commodities sold on the world market. M_{jr} is a constant elasticity of substitution (CES) combination of intermediate commodity inputs, where the amount of commodity i used by firm j in region r is x_{jr}^{i}. The composite is defined in equation 2. The parameter σ is a substitution elasticity between inputs in the intermediate composite. The parameters γ and ρ_{jr}^{i} are the CES scale and share parameters, respectively. The production function exhibits constant returns to scale (CRS) so $a_{jr} + b_{jr} + c_{jr} = 1 \; \forall \; j, r$. I assume a zero-profit condition, so cost must equal revenues, or

$$P_j Q_{jr}^s = P^K K_{jr} + w_{jr} L_{jr} + P_{jr}^M M_{jr}$$

Here, P_j is the price of output for the firm, P^K is the world price for capital, w_{jr} is the wage rate, and P_{jr}^M is the intermediate composite price, in industry j and region r. The price of the intermediate composite is calculated using optimal demands and input prices for each intermediate commodity.

Setting up the cost minimization problem and taking first order conditions gives the following demand equations:

$$K_{jr}^* = \frac{a_{jr}}{P^K} P_j Q_{jr}^s \tag{3}$$

$$L_{jr}^* = \frac{b_{jr}}{w_{jr}} P_j Q_{jr}^s \tag{4}$$

$$M_j^* = \frac{c_{jr}}{P_{jr}^M} P_j Q_{jr}^s \tag{5}$$

$$x_{jr}^{i\;*} = \frac{\rho_{jr}^{\sigma} P_{jr}^{D\,-\sigma}}{\gamma_{rj}^{\frac{\sigma}{1-\sigma}} \left(\sum_{i=1}^{J} \rho_{rj}^{i\;-\sigma} \; P_{rj}^{D\;1-\sigma} \right)^{-\frac{\sigma}{1-\sigma}}} M_j^* \tag{6}$$

Equations 3-6 define optimal demands for each firm j in region r. The variable P_{ir}^D is the domestic price buyers pay for good i. Note this can differ from the output price, P_j, due to tariffs.

2.3.b Household

Each region has a representative household that makes income from supplying capital and labor to firms as well as a government transfer. They then spend this income on final goods and services produced by firms. I assume that labor is internationally immobile and that it is sticky between industries. This is necessary for a fully non-Armington model to prevent perfect specialization. If employees could move between industries freely, all workers would simply move into the industry that paid the highest wages, and the country would completely specialize. Since we do not observe perfect specialization, I assume that workers have preferences over which industries they work in. The household problem is:

$$\max_{C_{ir}} U_r\left(C_{1r}, \ldots, C_{Jr}\right) = \prod_{i=1}^{J} (C_{ir})^{\theta_{ir}} \tag{7}$$

$$s.t.$$

$$\sum_{i=1}^{J} P_{ir}^{D} C_{ir} = \overline{w}_r \overline{L}_r + P^K K_r + \mathrm{T_r}$$

The consumer maximizes a utility function that is a Cobb-Douglas consumption function of goods from each industry $i = 1, \ldots, J$. The parameter θ_{ir} is the income share for good i in region r. The household earns price P^K on capital supplied, K_r, and an aggregate wage, $\overline{w}_r$, on total labor supplied, $\overline{L}_r$. In addition, households in each region receive a lump-sum transfer from the government, T_r. Shares of labor supplied to each industry are determined by the following exponential share equation.

$$l_{rj} = \frac{\exp\left(\eta_1 \ln\left(w_{rj}\right) + \eta_{2rj}\right)}{\sum_{i=1}^{J} \exp(\eta_1 \ln\left(w_{ri}\right) + \eta_{2ri})} \tag{8}$$

$$\bar{w}_r = \sum_{j=1}^{J} w_{rj} l_{rj} \quad and \quad L_{rj}^s = l_{rj} \times \bar{L}_r \quad \forall \quad j = 1, \dots, J$$

Equation 8 is a reduced-form labor supply equation. This function takes in two parameters. The first parameter is η_1, which is the elasticity of sector labor supply, L_{rj}^s, with respect to the sectoral wage, w_{rj}. The sectoral wage is determined in the production step using optimal demands given a set of world output prices and the world price of capital. After determining the sectoral wage from the firm's problem, households determine labor supplies to each industry.

At this point, I have created a world Arrow-Debreu economy that can be solved to find consumption and production in each industry and region. Consumption quantities come from solving for intermediate demands in the production step and consumption demands from the household. The sum of these is the total quantity of goods demanded by the region. Production quantities can be found using the optimal labor supplies to each sector from equation 8, and firms' optimal demand for labor from equation 4. In the next section, I use these quantities of production and consumption as inputs to an algorithm that estimates trade flows among the regions in the model.

2.3.c Trade Flows

Goods in this model are homogeneous by origin. Each good has a world market price, and firms in all regions receive the world market price. When consumers and firms purchase goods, they pay the world price plus any mark-up from tariffs. The problem with this model framework is that regions have no incentive to engage in cross-hauling. This is the act of a region importing and exporting the same good. Since this is a well-documented feature of international trade, I implement a new algorithm to predict trade flows between regions that incorporates this feature. I refer to the algorithm as a "gravity" model as it uses the observation from the gravity literature to predict trade flows. The gravity literature argues that trade integration between two countries tends to be correlated with their respective economic sizes and the distance between them (Deardorff 1998).

To set up the model, I assume that the modeler has information on total consumption and production for each region, but not information on price differentials. I assume that for each industry output j, a buyer in region r will meet a seller from region z with probability a_{rz}^{j}. In practice, this parameter is simply the share of imports from region z in total consumption for region r. I use this probability to create a matrix of estimated trade flows. I estimate the trade flow between regions r and z by multiplying the probability that region r is a buyer and the probability that r meets z.

$$\hat{F}_{rz}^{j} = D^{j}(n) \times a_{rz}^{j}$$

$$\sum_{z=1}^{R} a_{rz}^{j} = 1$$

The function $D^{j}(n)$ is simply the share of world consumption of good j that region r buys. Here, $\hat{F}_{rz}^{j}$ represents the probability that a given unit of total world production of commodity j is exported from origin region r as an import to destination region z. This gives the estimated trade flow matrix:

$$\boldsymbol{T}^j = \begin{pmatrix} \hat{F}_{11}^j & \cdots & \hat{F}_{1R}^j \\ \vdots & \ddots & \vdots \\ \hat{F}_{R1}^j & \cdots & \hat{F}_{RR}^j \end{pmatrix}$$

The rows of this matrix represent demand, and the columns represent supply. Thus, the imports from region 1 to region 2 can be found by looking at column 1 and row 2. The matrix also represents intraregional trade. Entries along the diagonal, $\hat{F}_{rr}^j$, are the amounts that region r consumes of its own production. To find the total estimated trade flows, one can simply multiply the matrix by total world consumption (or production) of good j. When calculating trade flows in a new equilibrium, I use the market-clearing amounts of consumption by region, and the probability of meeting is exogenously specified from a baseline of trade flows. For this matrix to be balanced, the rows must sum to the shares of world consumption, and the columns must sum to world production:

$$\sum_{z=1}^{R} \hat{F}_{rz}^j = D^j(n) \tag{9}$$

$$\sum_{n=1}^{R} \hat{F}_{rz}^j = S^j(z) \tag{10}$$

Here, $S^j(z)$ is the share of the world quantity of commodity j that region z produces. Since the probabilities I used to create the trade matrix sum to unity, the sum of row r of $\boldsymbol{T}^j$ is equal to $D^j(r)$, and the sum of regional demand equals total demand by construction. Supply, however, may not equal demand. Thus, equation 9 holds, but equation 10 may not. If equation 10 does not hold, then it is not a feasible allocation, and I need to adjust my estimate of trade flows to create a new matrix.

To redistribute trade flows and balance the trade matrix, I use an iterative method. When describing the sequential steps of the algorithm, I use a super script to denote which iteration the algorithm is on. For example, $\hat{F}_{rz}^{j(q)}$ is the trade flow calculated on iteration q. To begin the algorithm, I take my initial transportation matrix and define a vector of excess demands. This is the sum of trade flows in column z minus the production share in region z given by the CGE model.

$$\psi^{j(q)}(z) = \sum_{z=1}^{N} \hat{F}_{rz}^{j(q)} - S^{j}(z)$$

Excess demand for goods from region z is represented by $\psi^{j(q)}(z)$, and is the amount the trade flows matrix is overstating production in region z. In other words, region z does not produce enough to satisfy the trade flows estimated by the trade flows matrix in step q. Due to the construction of the matrix, the sum of excess demands is equal to zero at every step. This means that elements of excess production can be either positive or negative. For the matrix to be balanced and equation 10 hold, each element of excess production must be zero. To achieve this, I use a two-step updating process to redistribute trade flows. In the first step, I find the column with the largest positive excess production and update each element in the column by reducing it proportionally to trade flows calculated in the current iteration. The new column that replaces this column is calculated using the following formula.

$$\hat{F}_{rz}^{j(q+1)} = \hat{F}_{rz}^{j(q)} - \psi^{j(q)}(z)\ \frac{\hat{F}_{rz}^{j(q)}}{\sum_{i=1}^{R} \hat{F}_{iz}^{j(q)}} \tag{11}$$

This recursive equation updates the trade flow matrix column elements. On the right-hand side, the first term is the trade flow I calculated in the current iteration. The second term subtracts the excess demands from the region proportional to trade flows in the current iteration. For example, suppose 10% of production from region 1 went to region 2 according to the current trade matrix. If region 1 has positive excess demands, then I subtract 10% of excess demand for region 1 from the trade flows from region 1 to region 2, $\hat{F}_{12}^{j}$.

The reduction of the excess demands in the first step means that some regions shift their consumption to other regions. Thus, I need to increase consumption of other regions such that regional demand still sums to total demand (equation 9). This is done in the second step by updating the row elements in the transportation matrix.

$$\hat{F}_{rz}^{j(q+1)} = \hat{F}_{rz}^{j(q)} + P^{j}\big(r, z; \psi^{j(q)}(z) < 0\big)\left(\psi^{j(q)}(z)\ \frac{\hat{F}_{rz}^{j(q)}}{\sum_{i=1}^{R} \hat{F}_{iz}^{j(q)}}\right) \tag{12}$$

This recursive equation updates the trade flow matrix row elements of the columns that were not replaced by equation 11. The second term on the right-hand side is the mirror to the equation that updates the columns. The first part of the second term is the probability that region r will meet a buyer from region z given that region z has negative excess demands. This can be calculated using the trade matrix in the current iteration.

$$P^{j}\big(r, z; \psi^{j(q)}(z) < 0\big) = \frac{\hat{F}_{rz}^{j(q)}}{\sum_{i} \hat{F}_{ri}^{j(q)}}\ , i \in \{\psi^{j(q)}(z) < 0\}$$

This adjustment increases demands for regions that have negative excess demands, or demand that is less than their current production. The function increases quantity demanded from each other region proportionally to how much that region demands from regions that are overproducing. For example, suppose region 1 is the column adjusted using equation 11, which reduces the demand for goods from region 1. Suppose further that demand in region 2 for goods from region 1 is reduced by 1 unit due to this adjustment. If both region 2 and region 3 have negative excess demands, I shift this extra demand from region 2 to regions 2 and 3. If region 2 accounts for 90% of the demand from region 2 for output from regions 2 and 3, 0.9 units are shifted to region 2 and 0.1 units are shifted to region 3.

The last issue to confront here is how to incorporate explicit trade costs. This is an important question for this model because I am using it to determine the effect of changing tariff rates. I model the effect of trade costs by modeling the estimate of α_{rz}^{j} as a function of a baseline constant and tariffs.

$$\alpha_{rz}^{j} = \frac{\exp\left(ln\left(B_{rz}^{j}\right) - \omega\, ln\left(1 + \tau_{rz}^{j} - \hat{\tau}_{rz}^{j}\right)\right)}{\sum_{i=1}^{R} \exp\left(ln\left(B_{ri}^{j}\right) - \omega\, ln\left(1 + \tau_{ri}^{j} - \hat{\tau}_{ri}^{j}\right)\right)} \tag{13}$$

This is the exponential share function again. The denominator is the sum of the elements in numerator to normalize α_{rz}^{j} into a ratio. The parameter B_{rz}^{j} is the baseline share of consumption in region r that comes from region z. The second term in the exponential in the numerator is log of one plus the difference between tariff rates in the counterfactual τ_{rz}^{j} and tariff rates in the base case, τ_{rz}^{j}. This is then multiplied by a trade cost elasticity ω. If tariff rates in the counterfactual fall, then the α_{rz}^{j} will increase, indicating that buyers in region r are more likely to meet sellers from region z.

The algorithm terminates in a fixed number of steps, $R - 1$. This allows it to be implemented in a CGE model without fear of slowing down computational time. Additionally, the only parameters needed are baseline production quantities and trade flows to calculate α_{rz}^{j}, which can be done given information on all production and trade flows. The other necessary parameter is ω, which has several estimates in the literature. However, this parameter is only needed if one is modeling trade costs explicitly, such as tariffs.

2.3.d Comparison of Trade Models

The gravity algorithm generates empirically observed trade patterns using the distribution of supply and demand across regions. An example trade matrix for three regions is shown in the first panel of Table 2.1. Along the bottom row is the sum of the columns, which is the total share of world production for each region. Along the right-hand column are the sums of the rows, which are the total shares of world demand for each region. The elements of the matrix are the trade flows between regions. The question for the modeler is: given a new set of shares of world demand and supply, how do you estimate the elements of the matrix?

The following three panels in Table 2.1 show possible transportation matrices given a new distribution of supply and demand shares. In this case, I have simply flipped these vectors. The first panel shows the baseline matrix, which is the trade flows and total production and consumption in the baseline dataset. The following panels shows three different ways of estimating the trade flows (interior elements) using the supply and demand shares (row and column totals). The second panel shows the result from a net trade model. This means that there is no cross-hauling, and regions only engage in net trade. In this case, region 1 is the only net exporter, so region 1 satisfies all domestic demand and then exports any excess production. Regions 2 and 3 are net importers, so they export nothing to other industries and import the excess production from region 1. The net trade model is typically used by small open economy models, but it ignores cross-hauling, which is often most of international trade by volume.

Panel 3 of Table 2.1 shows the same exercise, except I use a different model to predict trade flows. In some sense, the shares of demand and supply can be viewed as probability mass functions. The share of demand for region 1 is the probability that any arbitrary unit of a good is purchased by region 1. Likewise, the share of production for region 1 is the probability that any

Table 2.1: Example Trade Matrices

Baseline Trade Matrix

	R1	R2	R3	Demand
R1	0.38	0.08	0.04	0.5
R2	0.02	0.23	0.04	0.29
R3	0.02	0.04	0.15	0.21
Supply	0.42	0.35	0.23	

Counterfactual Matrix: Net Trade

	R1	R2	R3	Demand
R1	0.42	0	0	0.42
R2	0.06	0.29	0	0.35
R3	0.02	0	0.21	0.23
Supply	0.5	0.29	0.21	1

Counterfactual Matrix: Naïve Model

	R1	R2	R3	Demand
R1	0.21	0.12	0.09	0.42
R2	0.18	0.10	0.07	0.35
R3	0.12	0.07	0.05	0.23
Supply	0.5	0.29	0.21	1

Counterfactual Matrix: Gravity Trade

	R1	R2	R3	Demand
R1	0.35	0.05	0.02	0.42
R2	0.08	0.21	0.06	0.35
R3	0.08	0.03	0.12	0.23
Supply	0.5	0.29	0.21	

Notes: These tables show different models predicting trade flows in a model using only the distributions of world supply and demand. For all matrices, the rows represent demand and the columns represent supply. The first panel is the baseline trade matrix, and the bottom three are models predicting trade flows with different demand and supply distributions. The net trade model only uses net exports and imports, the naïve model multiplies the two vectors, and the last panel uses the gravity trade algorithm.

arbitrary unit of a good was produced by region 1. One can then calculate the joint probability mass function by simply multiplying the marginal distributions together. I call this the naïve model. The matrix in panel 3 of Table 2.1 shows that this model generates a balanced matrix and cross-hauling, however it evenly distributes trade flows throughout the matrix. In contrast, the baseline matrix in panel 1 has much larger numbers along the diagonal. This is due to the phenomenon of home-bias, where countries tend to purchase more from domestic sources than foreign ones. I have not seen this model used in any trade models, however, it shows the main issue with including cross-hauling, which is how much to include.

Finally, panel 4 shows the results from using the gravity algorithm put forth in this paper to estimate trade flows. This creates a balanced matrix, so the equilibrium conditions still hold. It also generates cross-hauling, which is shown by the non-zero entries for net importers. It is also able to accommodate home-bias since this phenomenon is observed in the baseline matrix. Thus, the algorithm generates empirical observations about trade only using the distribution of regional supply and demand. The point of this exercise is to show the differences in the models, and why certain assumptions were necessary to achieve observations seen in trade data. In section 2.4.a, I use partial equilibrium models of this trade model to validate the gravity approach empirically.

2.3.e Government

There is a single government for each region that collects tariffs on imports and transfers all revenues lump-sum back to the household. I do not consider other tax policies such as taxes on labor and capital income, however any of these could be implemented with the correct data on tax rates and revenues. Governments also do not spend any money directly, however consumption shares in equation 7 are inclusive of government expenditures. Since the utility function is Cobb-Douglas, this is equivalent to a model that uses a constant share to split government transfers and spending.

Tariffs are charged on imports at the border so that the price the consumer pays is the world price plus the tariff. In a non-Armington model, the export supply curve is perfectly elastic, so importers bear the full burden of the tariff. To calculate the domestic markup on output from a particular industry, I use the trade flows from the previous section.

$$P_{ir}^{D} = P_i \times \left(1 + \sum_{z=1}^{R} \frac{\hat{F}_{rz}^{j}}{\sum_{i=1}^{R} \hat{F}_{iz}^{j}} \tau_{rz}^{i}\right)$$

The final price to domestic buyers of good i in region r is equal to the world price of that good, P_i times an ad valorem tariff markup. The second term in the parentheses on the right-hand side is the markup on the world price. For a given region r, the share of consumption subject to a tariff on goods from region z is given by trade flows from z to r, $\hat{F}_{rz}^{j}$expressed as a share of all trade flows to r, $\sum_{i=1}^{R} \hat{F}_{iz}^{j}$. This share of consumption is then multiplied by the ad valorem tariff rate on goods imported into region r from z, τ_{rz}^{i}. Recall that it is possible that $z = r$, so all domestic consumption has a tariff rate of zero or $\tau_{rr}^{i} = 0$. Finally, total revenues collected on tariffs are equal to

$$Rev_r = \sum_{i=1}^{J} P_i \times \left(\sum_{z=1}^{R} \frac{\hat{F}_{rz}^{j}}{\sum_{i=1}^{R} \hat{F}_{iz}^{j}} \tau_{rz}^{i}\right) \times \left(C_{ir} + \sum_{j=1}^{J} x_{jr}^{i}\right) \tag{14}$$

Each term of the summation on the right-hand side is simply the world price times the total tariff markup times the total consumption of good i. For each i this is the total tariff bill collected on consumption of that good in region r. I then sum over all goods to find the total revenue from tariffs for region r.

2.3.f Equilibrium

Equilibrium in this model is an allocation where all goods and factor markets clear given each agents' optimal conditions, government transfers, and trade costs. Formally, the equilibrium conditions are

$$\sum_{r=1}^{R} Q_{ir}^{s} = \sum_{r=1}^{R}\left(C_{ir} + \sum_{j=1}^{J} x_{jr}^{i}\right) \quad \forall \quad i = 1, \dots, J \tag{15}$$

$$L_{jr}^{*} = L_{jr}^{s} \quad \forall \quad j = 1, \dots, J \quad and \quad r = 1, \dots, R \tag{16}$$

$$\sum_{r=1}^{R}\sum_{j=1}^{J} K_{jr}^{*} = \sum_{r=1}^{R} K_{r} \tag{17}$$

$$\mathrm{T}_{r} = Rev_{r} \quad \forall \quad r = 1, \dots, R \tag{18}$$

Optimal household demands for final consumption can be determined from equation (8) and intermediate demands for production can be determined from equations (5) and (6). Taking these together forms the goods market clearing condition in equation (15). Sectoral labor supplies from equation (8) are equal to sectoral labor demands from equation (4) for all regions. Capital is internationally mobile, so equation (17) clears the capital market by ensuring that the sum of all capital demands for all industries and regions is equal to the sum of all capital supplied by households. The last equation is the balanced budget constraint on the government. Equation (18) simply says that all government revenues are transferred to households.

The model is solved in an iterative two step process. First, I make an initial guess for the transportation matrix and calculate trade flows and costs based on this guess. Second, I solve the

CGE model for a market clearing equilibrium using Merrill's variant of Scarf's algorithm. Once the algorithm has found the market clearing allocation, I run the transportation matrix algorithm presented in the previous section and check it against my guess. If the difference is larger than a preset tolerance, I use the updated transportation matrix as my new guess and return to the first step. The program terminates when an equilibrium is found that is sufficiently close to the "guessed" trade matrix. This implies that all agents have perfect knowledge of all trade flows and costs in the final equilibrium.

2.4 Data and Calibration

To calibrate the model, I create social accounting matrices for each country using data from the World Input-Output Database (WIOD). I include four countries in my model: Canada, Mexico, the United States, and China. While China was not a member of NAFTA, they embraced a more open trade policy during this time and became a strong trade partner with all three member countries. The remaining countries are combined into a single region defined as the Rest of the World (RoW). The WIOD contains information on production over 35 industries and 40 countries. I take the disaggregated world input-output matrix and aggregate it to 20 industries and the 5 regions mentioned above (3 member countries plus China and RoW). The aggregated industries are reported in Table 2.2, along with import and export information for each industry for the United States. I define the period of my study as the ten-year period after NAFTA was implemented, 1995 to 2005. While NAFTA was ratified the year prior to the start of this period (in January 1994), 1995 was the earlier year in my dataset.

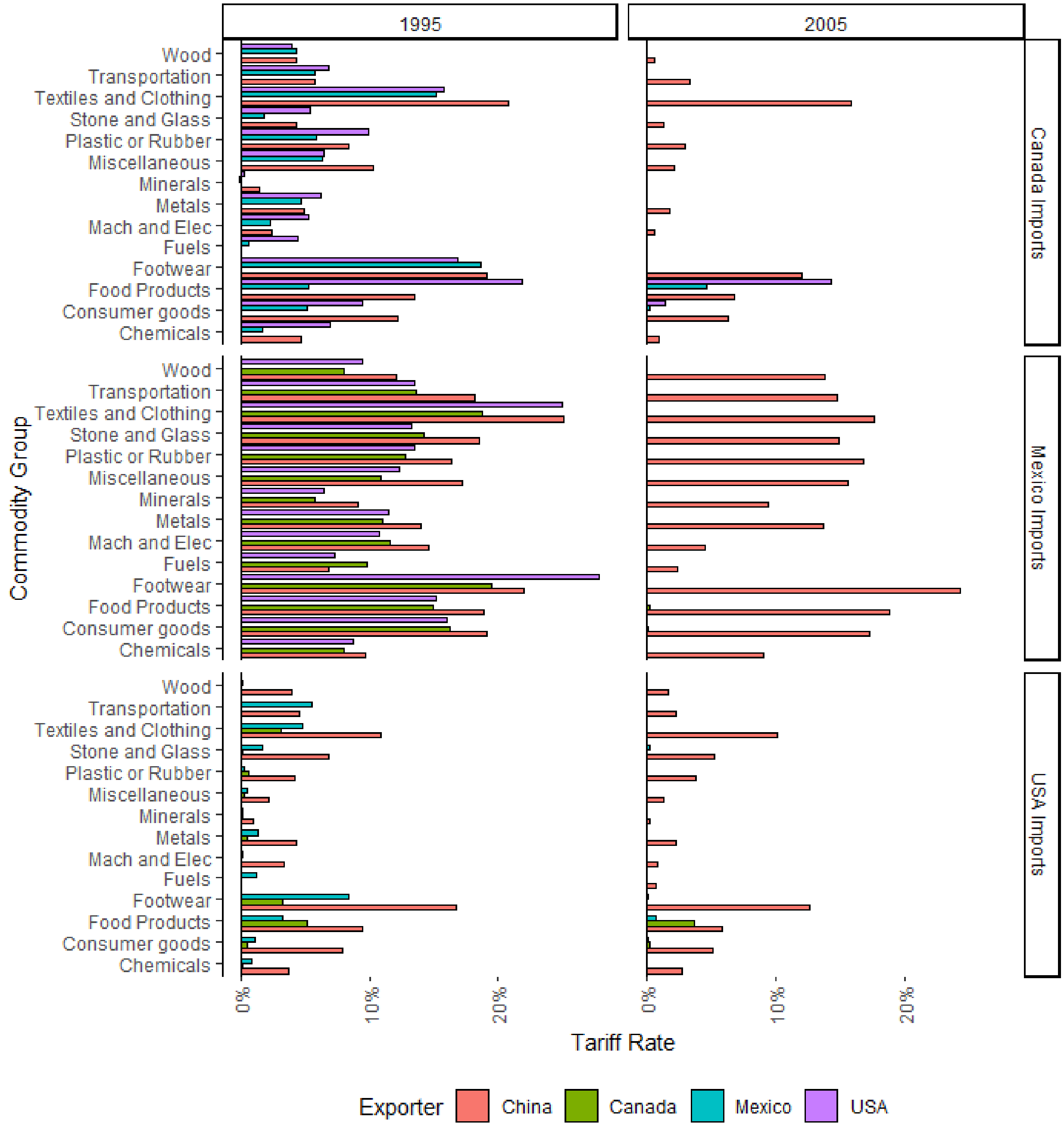
Table 2.2: United States Trade Statistics for 1995 (in millions of $US 2013)

Industry	Imports	Exports	Net Exports
Agriculture, Hunting, and Fishing	$20,984.98	$27,256.18	$6,271.21
Mining and Quarrying	$48,006.81	$10,031.94	-$37,974.87
Food Products	$23,009.11	$32,342.49	$9,333.38
Textiles and Clothing	$53,416.78	$13,070.08	-$40,346.70
Footwear and Leather	$19,025.88	$967.37	-$18,058.51
Wood	$10,758.53	$4,805.96	-$5,952.57
Paper and Pulp	$24,676.88	$28,174.57	$3,497.69
Fuels	$9,946.21	$9,560.86	-$385.35
Chemicals	$52,476.24	$52,935.49	$459.25
Plastic or Rubber	$14,925.65	$10,915.90	-$4,009.75
Stone and Glass	$10,420.85	$5,235.23	-$5,185.62
Metals	$51,782.01	$29,378.16	-$22,403.84
Machinery and Electrical Equipment	$238,263.56	$188,550.82	-$49,712.74
Transportation Equipment	$120,382.65	$90,736.88	-$29,645.77
Miscellaneous Manufacturing	$33,373.04	$12,537.08	-$20,835.96
Utilities and Construction	$2,184.59	$443.54	-$1,741.05
Consumer goods	$6,413.18	$79,838.22	$73,425.04
Transportation Services	$21,553.41	$64,628.68	$43,075.26
Business Services	$5,971.33	$15,434.15	$9,462.83
Consumer Services	$68,681.13	$88,381.72	$19,700.58
Total	$836,252.81	$765,225.32	-$71,027.49

Notes: This table shows all industries and their respective volumes of import and exports. The final column shows net exports. All values are in millions of $US.

Tariff data comes from the World Integrated Trade Solution (WITS) database. Specifically, I use the weighted tariff measure by commodity, origin, and destination. The change in tariffs between 1995 and 2005 is shown in Figure 2.1. The left side of panels shows tariff rates for each commodity in 1995, and the right panel shows tariff rates for those same industries in 2005. Almost all tariff rates between the NAFTA countries have dropped to zero. This is expected, as all tariff rates for this Free Trade Area fell to zero by 2004 per the conditions of NAFTA. The commodity definitions between WITS and WIOD are not exactly direct, so I

Figure 2.1: Tariff Rate Changes 1995-2005 for Manufacturing Industries



Notes: This figure shows all tariff changes for NAFTA member countries with their respective member partners and China. The left panel shows tariff rates in 1995, the start of my analysis, and the right panel shows the same rates in 2005, the end of my analysis. Agriculture tariffs in 1995 were well over 40% for some countries so they are omitted for visibility.

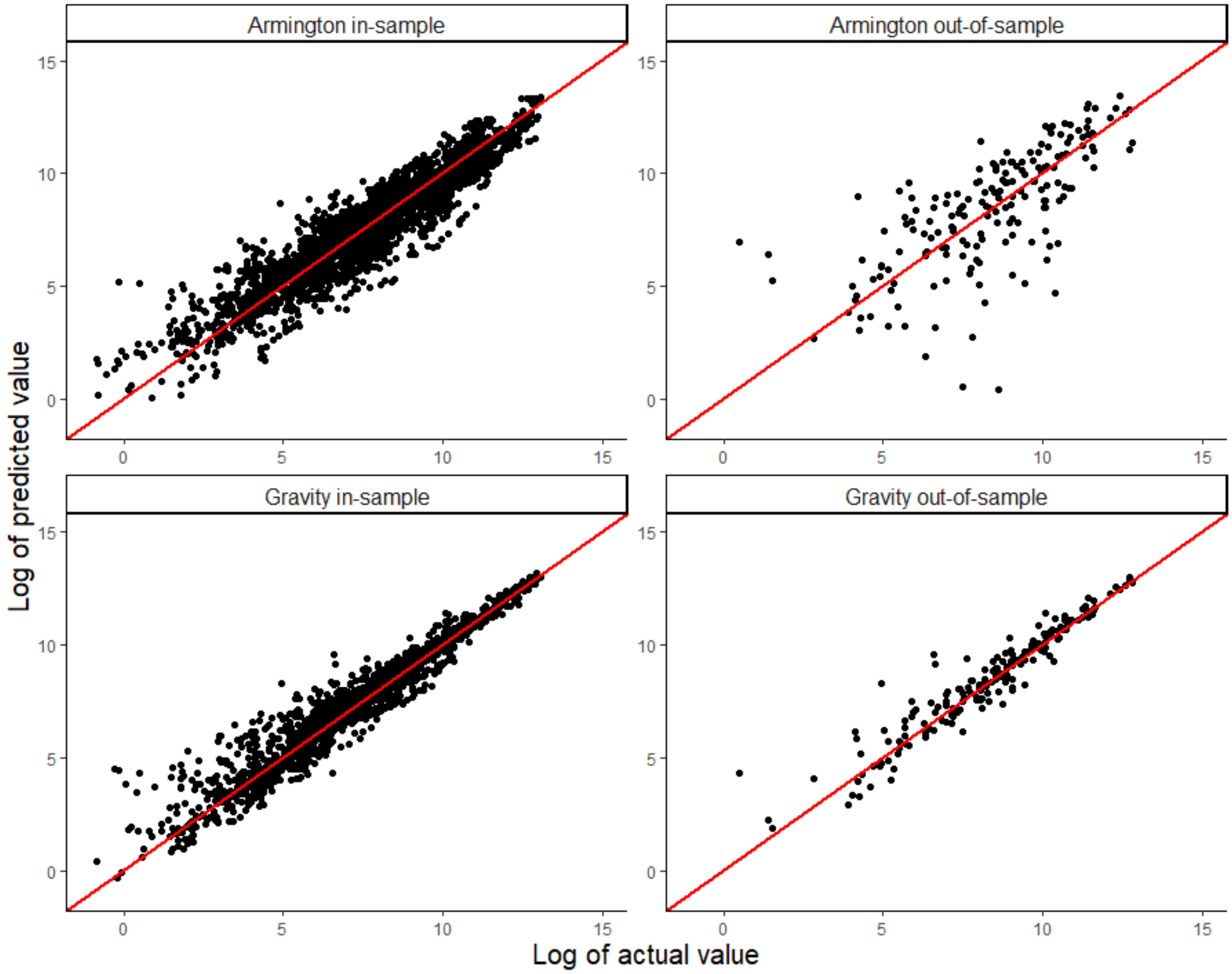
create a crosswalk between WITS and WIOD. The mapping between industries are shown in appendix Table B.1.

The model is calibrated by first setting elasticity parameters using my estimates or taking estimates from previous literature. The elasticity of substation over intermediate goods, σ, is set to 0.5. Parameters of the top level of the Cobb-Douglas production function, $a, b,$ and c, are set according to expenditure shares in production. These are unique to each industry and region and based on social accounting matrices I built from WIOD data. The labor sector elasticity parameter is set to 1.22 according to the estimation in chapter 1. The impact of trade costs on trade flows in equation is determined using the tariff elasticity, ω, which partly determines changes in trade flows in the gravity algorithm. I use a value of 7.7, which is the average trade elasticity measured by Hertel, Hummels, Ivanic, and Keeney (2007). Other papers use a higher elasticity, such as Caliendo and Parro (2015), who also study NAFTA and use an average trade elasticity closer to 11. In the results section I run the simulation again under higher and lower elasticities to test the sensitivity of my results to these parameters.

2.4.a Empirical Comparison of Armington and Gravity Model

The gravity model I put forward in section 2.3.c is a new one, even though it has largely the same form as previous gravity models in the literature. In this section, I test it empirically in partial equilibrium to ensure it reliably predicts trade flows. I use data on production, consumption, prices, and trade flows among the 5 regions in my dataset for 20 commodity categories for the years 1995 to 2011. Using consumption and production quantities, I predict trade flows using the gravity model. Using prices, I predict the same trade flows using the Armington model. Information on how I estimated the models can be found in Appendix A. I compare the two models with standard techniques to assess the goodness of fit. First, scatterplots of actual vs. predicted values is presented in Figure 2.2. The left column of panels show the

Figure 2.2: Trade Flow Prediction Accuracy of Armington and Gravity Model



Notes: This figure plots predicted trade flows against actual trade flows organized by model type and sample used. The top two panels show the prediction from the Armington model and the bottom panels show the prediction from the gravity model developed in this paper. This figure is intended to show that the gravity model I use is at least as accurate as the Armington model in predicting trade flows.

Armington and gravity models' performance when I use the full dataset to estimate the parameters in the model. The right column shows the performance of predicted outcomes for only 2011 using data from before 2000. The purpose of these graphs is to see how the models perform in out-of-sample prediction.

Visually, the gravity model performs better than the Armington model in predicting trade flows. This is confirmed by goodness-of-fit statistics: R-squared for the Armington in-sample model is 0.66 and for the gravity model it is 0.95. Additionally, the mean squared error (MSE) of the Armington in-sample prediction is 7.95×10^8 and for the gravity model MSE was 0.8×10^8. This is not surprising as gravity models are often lauded for their accuracy in the trade literature. Employing the gravity model empirically may be difficult in some scenarios since information on production, consumption, and trade flows for the entire world is needed to parametrize and run the model. However, it works well with this CGE model and predicts trade flows at least as well as, or better than, the Armington model.

2.5 Results

To simulate NAFTA, I use the typical practice in applied general equilibrium of simulating a baseline scenario where tariffs are kept at their 1995 levels. I then simulate a counterfactual scenario where tariffs are reduced to their 2005 levels. Note that I include all tariff reductions for the counterfactual scenario, so in some sense it is not a pure evaluation of NAFTA. However, tariff changes with partners outside of NAFTA were much smaller than those with partners inside.

To compare these results to the simulations used in Kehoe (2005), I have recreated his methodology in comparing simulation results to the data. He does this by using simple linear regression between the data and the model. Specifically, the model he estimates is

$$data_i = a + b \times model_i + \epsilon_i$$

Where $data_i$ is the vector of changes observed in the data, and $model_i$ is the vector of changes predicted by the model. The parameter a is the intercept and b is the slope of the regression line between the results from the data and the results from the model. If the model perfectly predicted the data, then the slope would be one and the intercept would be zero. So, the deviation of these estimated parameters from those values indicates how well the model predicts the changes seen in the data. The slope shows how well the magnitudes in the data and model predictions match each other. The intercept shows how far the overall averages are from each other. Kehoe does not include which of these is the more important statistic, but they both contain information on prediction accuracy.

Table 2.3 presents the results on overall changes in trade flows between NAFTA members. The first column shows the changes that are observed in the data. These are expressed in terms relative to GDP. Since my model is not dynamic, I am not accounting for economic growth in the model. However, this follows directly from Kehoe's methodology. The second column shows the changes in trade predicted by my CGE model. The model correctly predicts that the largest changes will be on Mexico. However, the model underpredicts changes in Canadian trade flows by about half. The model also underpredicts the large increase in US imports. However, this large change may have been due to large capital inflows into the US, which the model does not account for.

Table 2.3: Total Trade Flow Results from NAFTA Simulation

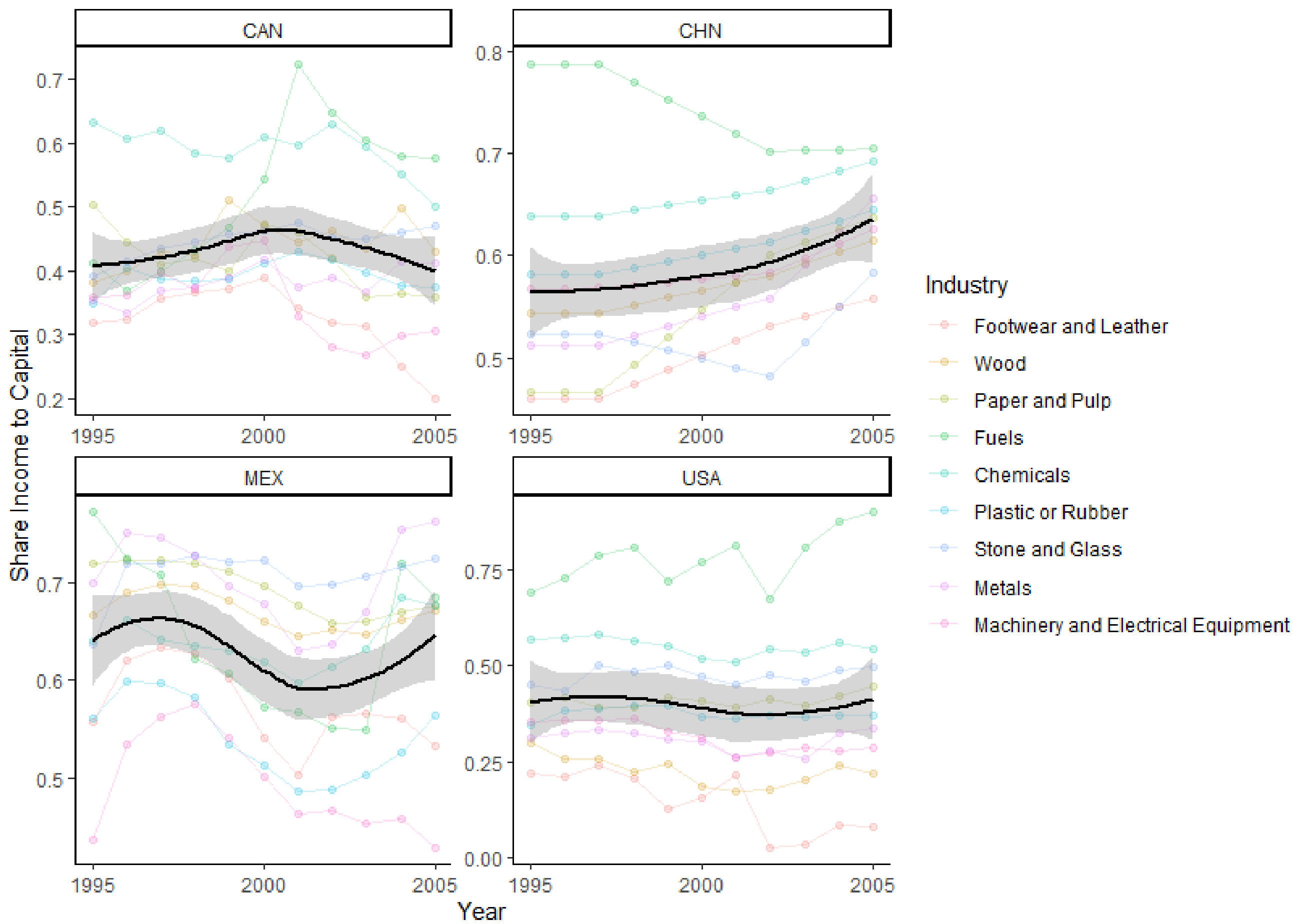
Trade Flow	Data	Tariff Change Only	Tariff Change & Tech. Change	Brown-Deardorff-Stern
Canada Imports	46	23	19	4
Canada Exports	47	24	25	4
Mexico Imports	88	59	61	34
Mexico Exports	71	77	81	51
USA Imports	71	24	25	2
USA Exports	24	23	27	3
China Imports	141	59	111	-
China Exports	152	79	79	-
	Slope	1.36	1.09	2.43
	Intercept	17.41	21.90	23.20
	Correlation	0.75	0.82	0.64

Notes: This table shows trade flows changes for each of the directions listed in the left column. The second column is the changes in trade in the data relative to GDP growth. The third and fourth columns are predictions from the non-Armington model, and the last column is the prediction from the BDS model from Kehoe (2005). The regression statistics at the bottom indicate the how well the predictions fit the data. If the predictions perfectly fit the data, the slope would be 1, the intercept would be 0, and correlation would be 1. Deviations from these values determines how well the prediction matches the data.

The results on trade flows for China show that the perfect substitutes model does underpredict trade changes in China. Much of this is likely because I am not including any form of technological change during the sample period. China, however, went through a fast industrial revolution during this time. This is shown in Figure 2.3, where I plot the share of value-added income that went to capital in each year. While NAFTA members varied slightly over the period, on average, all of them ended up at roughly the same point in 2005 that they were at in 1995. The major exception is China, who experienced capital-biased growth in manufacturing sectors. This rapid change resulted in an increase of 10 percentage points in the share of income going to capital.

To see how this affects my results, I run a second simulation where I change the tariff rates and parameters in the production function. In the counterfactual simulation, the parameter on capital is increased by 10 percentage points for and the other parameters are decreased to maintain constant returns to scale. This change is only for manufacturing firms in China. The results are presented in the second column of Table 2.3. Trade changes for China are much larger

Figure 2.3: Capital Income Shares in Manufacturing Industries During NAFTA



Notes: This figure shows the share of value-added income that went to capital in each year from 1995-2005. This includes only select manufacturing industries; however, these were industries that experienced large changes in tariffs. While NAFTA member countries, Canada, Mexico, and the US ended in about the same place, China saw a general increase over this period.

under this specification, and the regression results indicate a slightly better fit to the observed trade changes. The slope of the regression line falls to 1.09, the intercept increases to 21.9, and the correlation coefficient increases to 0.82. Interestingly, trade flow changes in the NAFTA member countries are not heavily impacted by the technological change. Trade flow changes are about the same as they were when I only considered the change in tariffs.

To compare this to simulations used in Kehoe (2005), I also include his results from simulations of the Brown-Deardorff-Stern (BDS) CGE model analyzing the effects of NAFTA. While this model used a different time period, 1988 to 1999, the changes in trade were of similar magnitudes. To make a more direct comparison, I use the regression results from the original paper. The first observation that stands out is how much smaller the magnitudes are than the data and the perfect substitutes model. Mexico is the only country whose trade changes hit double digits. This is confirmed by the statistics from the regression model. The slope of the regression line for the perfect substitutes model is 1.34 and the intercept is 17.5. Compared to the results from the BDS model, which has a slope of 2.43 and an intercept of 23.2, the perfect substitutes model does a better job of capturing the magnitude of changes from NAFTA. We can also compare the fit of the model to the data using the Pearson correlation coefficient. The perfect substitutes model is able achieve a correlation coefficient of 0.75, which is slightly higher than the correlation for the BDS model of 0.64.

Table 2.4: Results on Exports from NAFTA Simulation

		Exports to:	
		Mexico	USA
	Data	27.62	394.27
Canada	Non-Arm.	21.75	90.99
	BDS	-0.22	49.80
		Canada	USA
	Data	128.08	2.90
Mexico	Non-Arm.	227.35	84.47
	BDS	3.98	0.29
		Canada	Mexico
	Data	70.70	38.37
United States	Non-Arm.	4.41	22.32
	BDS	19.96	1.24
		Slope	Intercept
	Non-Arm.	0.5	72.4
	BDS	6.8	25.2

Notes: This table shows exports between NAFTA members and their respective member partners. For each table, Data is the observed change in the data, Non-Arm. is the prediction from the non-Armington model, and BDS is the predicted changes from Kehoe (2005). The last two rows show the slope coefficients between the data and the model like in Table 2.3.

I can also compare specific trade relationships to those presented in Kehoe (2005). Exports for the NAFTA member countries and their member partners are presented in Table 2.5. There are three sections in the table that present trade changes for Canada, Mexico, and the United States. Note this differs from Table 2.3 by reporting changes with specific partners rather than overall trade. I use the results from the simulation only taking into account the tariff changes, and I am not including the technological change in China. The non-Armington model is able to generate large changes in trade here as well. While I overshoot changes in exports from Mexico to the US and changes in exports from the US to Canada, I am able to generate the large changes in trade seen in Mexico and Canada. Results from the BDS model show the contrast of changes. The BDS model mostly predicts small, single-digit changes from Mexican exports (less than 10%), and the non-Armington model is able to generate changes of over 100%. On average, the non-Armington model under predicts the changes in trade by about 32% and the BDS model under predicts trade by 89%. The regression statistics confirm this, while the BDS model has a lower intercept than the non-Armington model, the slope is much higher, indicating a poor fit with the magnitudes observed in the data.

In the last set of results, I explore other effects of NAFTA to show how the model can be used to analyze the effects of NAFTA. In Table 2.4, I present changes in labor demands for each sector in the four countries of my study. Again, these results are from the simulation only including the change in tariffs and does not include the technological change from China. All countries see a decline in labor demand for the agriculture sector as production shifts to the Rest of the World region. The biggest changes are for Mexico and China in the manufacturing sectors. Both see large increases in labor demand for clothing manufacturing like Textiles and Clothing and Footwear and Leather. However, there are also large increases in demand in Mexico for Metals, Machinery and Electrical Equipment, and Transportation equipment. The US sees the smallest changes in labor demands across all countries. Overall, the US sees a 0.04% reduction labor demand in the manufacturing sectors and a 0.01% increase in the services sectors. This is likely because the US already had low tariffs in 1995 compared to Mexico and Canada, which can be seen in Figure 2.1. So, gains from reducing tariffs are likely smaller in the US than Canada and Mexico.

Table 2.5: Labor Demand Impacts from NAFTA Simulation

Industry	China	Canada	Mexico	USA
Agriculture, Hunting, and Fishing	-3.0%	-3.1%	-1.8%	-0.2%
Mining and Quarrying	-0.3%	0.3%	-2.2%	0.2%
Food Products	-4.1%	-3.8%	13.4%	0.1%
Textiles and Clothing	18.1%	6.7%	44.6%	-0.2%
Footwear and Leather	34.5%	3.6%	13.3%	-1.1%
Wood	4.6%	-6.2%	6.3%	0.1%
Paper and Pulp	1.8%	0.8%	6.8%	0.0%
Fuels	1.2%	4.3%	-1.0%	0.3%
Chemicals	1.7%	4.3%	0.2%	0.1%
Plastic or Rubber	9.0%	3.6%	6.4%	-0.2%
Stone and Glass	0.2%	1.0%	-2.6%	0.1%
Metals	1.3%	5.0%	17.3%	0.2%
Machinery and Electrical Equipment	9.7%	5.2%	37.6%	-0.2%
Transportation Equipment	14.3%	14.7%	33.5%	-0.3%
Miscellaneous Manufacturing	10.0%	1.9%	15.0%	0.0%
Utilities and Construction	-0.5%	1.0%	-0.3%	0.0%
Consumer goods	-0.8%	-0.5%	-2.6%	0.0%
Transportation Services	-0.6%	-0.8%	-3.2%	0.0%
Business Services	-1.9%	-1.1%	-4.8%	0.0%
Consumer Services	-0.7%	-1.1%	-4.1%	0.0%
Total Manufacturing	5.77%	3.96%	16.47%	-0.04%
Total Services	-1.01%	-0.77%	-3.63%	0.01%

Notes: This table shows the changes in labor demand predicted by the non-Armington model. All values represent changes between the baseline equilibrium and the counterfactual equilibrium. Note that total labor supply is set in this model, so total labor demand changes are zero.

Changes in capital demands tell a similar story. Capital use by firms in the US drop across all sectors. Mexico, on the other hand, experiences huge capital inflows, particularly in the manufacturing sectors. Textiles and Clothing doubles its capital use and Machinery and Electrical Equipment increases capital by 87%. Overall, capital demand for manufacturing industries jumps by 32%. Canada also experiences an increase in capital use, albeit smaller than Mexico at 7.9%. Lastly, China also experiences large capital inflows. While other countries experienced a marked shift of capital from services to manufacturing, both sectors increase capital use in China. The manufacturing sectors increase capital demand by 11.2% and demand for capital in service industries increases by 1.1%.

The model presented here is highly abstract, and it is only presented in a static context. However, in future research, a dynamic portion could be added to adjust factors over time. This would provide a more realistic evolution of capital by including a market for savings and investment. In addition, more realism could be added to the labor market. In this model, I assume that total labor is supplied inelastically and workers use sectoral wages to decide how to allocate labor across sectors. This could be altered to include a labor-leisure choice or even possibly involuntary unemployment. While this would provide a better theoretical foundation for the model, several aspects of free trade agreements can be generated even using this simple model.

2.5.a Sensitivity

I now turn to sensitivity checks to see how robust the model is to changes of parameters that I either estimated or took from the literature. To test the model under these changes, I select a new parameter value and recalibrate the model changing only that parameter. I choose three parameters, the tariff elasticity, the substitution elasticity in the intermediate composite, and the labor sector elasticity. While the model technically uses hundreds of parameters in the production functions, consumption composites, and trade flow matrices, these are all pinned down by the dataset. The model is built such that I choose a set of elasticity parameters and then solve for the remaining parameters assuming that the baseline dataset represents an equilibrium allocation.

The results from the sensitivity analysis are shown in Table 2.6. This table recreates the main results in Table 2.3. The first two columns are the changes observed in the data and the baseline specification. The next two columns show the changes when the trade elasticity is set to 5.5 and 11. The lower value 5.5 is taken from Hertel (2007). The authors argue that this value is average elasticity that previous versions of the CGE model GTAP used, as compared to the updated model that uses an average value of 7.7. The second value of 11 comes from Caliendo and Parro (2015), who use an Eaton-Kortum model to estimate trade elasticities.

The results from these two specifications indicate that my model is the most sensitive to these parameter values. Trade changes are muted when the trade elasticity is set to 5.5 and much higher when the elasticity is set to 11. However, the magnitudes of the changes are still higher than those predicted by the BDS model, even when using the lower trade elasticity value. The relative distribution of changes remains largely the same – Mexico and China experience the largest trade impacts. The proportional change in trade changes is about the same as the proportional change in trade elasticities. Doubling the trade elasticity from 5.5 to 11 causes about a doubling of the magnitudes of the predicted changes.

The next three columns show the results from simulations where the elasticity on the intermediate composite is changed. I consider three values: 0.25, 0.75, and 1.25. Although smaller values of this elasticity give more muted changes, the differences between the specifications are very small. The final two columns show results from changing the labor sector elasticity. While access to labor markets and movements between them drive a lot of the comparative advantage in this model, the differences between the two models are surprisingly small. Additionally, a smaller labor sector elasticity leads to a slightly different distribution of

Table 2.6: Sensitivity Results

	Data	Baseline	Tariff Elasticity 5.5	Tariff Elasticity 11	Production Elasticity 0.25	Production Elasticity 0.75	Production Elasticity 1.25	Labor Elasticity 0.25	Labor Elasticity 2.5
Canada Imports	46	23	15	30	23	24	23	21	23
Canada Exports	47	24	16	31	24	25	25	23	25
Mexico Imports	88	59	34	86	58	59	63	60	58
Mexico Exports	71	77	49	105	74	78	82	79	77
USA Imports	71	24	16	28	21	22	23	22	22
USA Exports	24	23	15	28	21	21	22	22	22
China Imports	141	59	23	100	61	65	69	67	63
China Exports	152	79	39	124	82	85	86	87	78
	Slope	1.36	1.63	0.92	1.36	1.31	1.24	1.26	1.37
	Intercept	17.41	37.64	18.67	17.73	17.71	18.76	19.58	16.84
	Correlation	0.75	0.48	0.83	0.78	0.79	0.78	0.79	0.77

Notes: This table presents sensitivity analysis for the model. For each column, the columns in Table 2.3 are replicated under different elasticity assumptions. The first two columns come from Table 2.3. Columns 3 and 4 vary the tariff elasticity, columns 5-7 vary the production elasticity, and columns 8 and 9 vary the labor sector supply elasticity. Regression statistics are calculated for each column as in Table 2.3.

trade changes. Increases in trade for Mexico and China are smaller and increases for Canada are slightly higher.

For the most part, the conclusion that we see larger changes in trade from a non-Armington model seems robust to most parameter choices. However, much like Armington models, the changes in trade are most sensitive to the choice of trade elasticity. Getting estimates of trade elasticities is inherently difficult. Some researchers have argued that the use of price differentials instead of trade costs have led to smaller elasticities. Going forward, I may be able to use tariff changes to estimate trade elasticities rather than price differentials to fit this model. If tariff changes are assumed to be exogenous, then the impact on trade flows can possibly be identified. However, the trade elasticity question seems to remain a difficulty of trade model calibration.

2.6 Conclusion

As more countries continue to embrace free trade, governments will want to analyze the effects of such agreements. CGE modeling is a natural choice for this work since it can be used to perform counterfactual policy analysis. In addition, CGE analysis can be used to analyze the distribution of effects across sectors. When applied to international trade, many CGE models use the Armington assumption to model trade. Recent evaluations of the Armington model have identified some questions about its applicability to policy changes, especially free trade agreements. The use of the Armington assumption in analysis of free trade agreements may lead to muted changes in trade.

In this paper, I create a non-Armington CGE model with homogeneous goods that includes trade flows. I prevent perfect specialization by including frictions in the labor market, as previous models have done. I extend the literature by including an algorithm that predicts trade flows using the distribution of regional consumption and production instead of price differentials. This allows me to include empirically observed trade phenomena such as cross-hauling and home-bias in a homogeneous goods model. The model I specify is highly abstract, production and utility functions are Cobb-Douglas and government interactions are minimal. Even using this model, I can generate larger changes in trade than CGE models using the traditional Armington assumption.

The non-Armington model has several desirable features that may make it useful in policy analysis in other areas of research. One extension is creating a state-level model for the US. This would allow analysis how policy impacts are distributed geographically. In addition, models of regional migration could be included to determine the impact of labor mobility between states. Other applications could be for situations where the modeler has reason to believe the region in question has very little impact on world prices. The non-Armington model is a useful framework in these cases, and using the algorithm developed in this paper, multi-lateral trade flows can be included in such a model. In future research, I plan to look for new policy applications and improve the empirical strength of the algorithm predicting trade flows.

Chapter 3: The Clean Air Act Amendment and Missed Work

3.1 Introduction

In 1963 the Clean Air Act was signed into law by Lyndon B. Johnson. It was one of the first regulations of air pollution at the federal level in the United States. Researchers have since worked to examine the impacts on the labor market. Typically, this is framed in a simple benefit-cost analysis. Labor costs are employment losses and sectoral reallocations from production restrictions. However, labor supply can also increase on the intensive margin. Improved health for workers could mean higher productivity at work. Workers may increase attendance, or they may be more productive while on the job.

The literature on the effect of the Clean Air Act on employment shows a consistently negative impact on the quantity of labor supplied and demanded in affected industries. Greenstone (2002) used the initial Clean Air Act Amendment of 1970 to identify an environmental policy impact and found that regulated counties lost 590,000 jobs in comparison to unregulated counties. Another study by Walker (2013) looks closer at the transitional costs employees face when regulation destroys jobs in the polluting sector. He finds that workers who leave the industry after regulation receive a lower wage in their new industry, on average. The present value of total forgone earnings for those separated from their firm is equal to 1.2 times one year of pre-regulatory earnings.

Other studies have explored the public health impacts of the Clean Air Act using various measures. One of the first studies to do this was Greenstone (2003) which looked at the effect on infant mortality rates. He found that a 1% reduction in total suspended particles led to a 0.3% reduction in infant mortality rates. A working paper from Bishop et al. (2018) analyzed the effect of PM 2.5 on Alzheimer's disease using the 2004 Clean Air Act Amendment to identify the policy effect. They find that a 1 microgram per cubic meter increase in particulate matter exposure led to a 3% increase in dementia cases.

Recently there has also been work on how pollution affects labor supply and productivity. If pollution damages health status, then workers may need to take more sick days, or it could make their jobs more difficult. One recent study found that exposure of 25 days or more to 10 ppb increased PM 2.5 reduced the productivity of manufacturing workers in China by about 1% (He et al., 2019). Another earlier study found slightly larger effects when focusing on agricultural workers; increased ozone levels contributed to a 4% loss in productivity (Zivin and Neidell, 2012). Another paper used data on German football players and air pollution at matches and found a negative impact on measures of player productivity (Lichter et al. 2017).

Previous research on the connection between air pollution and labor supply have looked at short term changes in pollution and "restricted activity days" or RADs. This term encompasses work lost due to air pollution and days spent in bed. Most of these studies use the National Health Interview Survey (NHIS) conducted by the Center for Disease Control (CDC). Ostro and Rothschild (1989) and Ostro (1987) are commonly cited studies in discussions about RADs. These papers have also commented on at-work productivity in the form of "minor restricted activity days" or MRADs. MRADs are when a worker can attend work but reports limitations in being able to perform tasks. Other studies such as Hausman and Ostro (1984) have considered the impact of pollution on missed days at work using Poisson modeling.

More recently, a paper estimated the causal effect of pollution on labor supply by examining workers in Mexico City. The subjects lived near a polluting factory that closed suddenly and led to a decrease in pollution in the nearby area. Using this quasi-experiment, the author was able to estimate that a 20% decline in sulfur dioxide concentrations led to a 1.3-hour increase in work attendance the following week (Hanna and Oliva 2015). Another paper considers long term effects by exploiting variation in the Clean Air Act Amendment. The authors find that earnings and labor force participation are reduced later in life for people born in higher pollution areas (Isen, Rossin-Slater, and Walker 2017).

Researchers have not estimated the effect of the CAAA on labor supply directly; however, the EPA has considered this benefit in their report on the CAAA. They estimate that without the CAAA 17 million workdays would have been lost due to illness in 2010 for which they assessed the value at $2.7 billion. This number was reached by looking at income losses due to diseases caused or exacerbated by air pollution. Using BenMAP, an air pollution simulation model, they predict the effect of regulation on pollution and the incidence of respiratory diseases. The EPA converts this income loss into days of work missed using average wage rates. However, no direct empirical measure of the impact of CAAA on lost workdays due to illness exists to my knowledge.

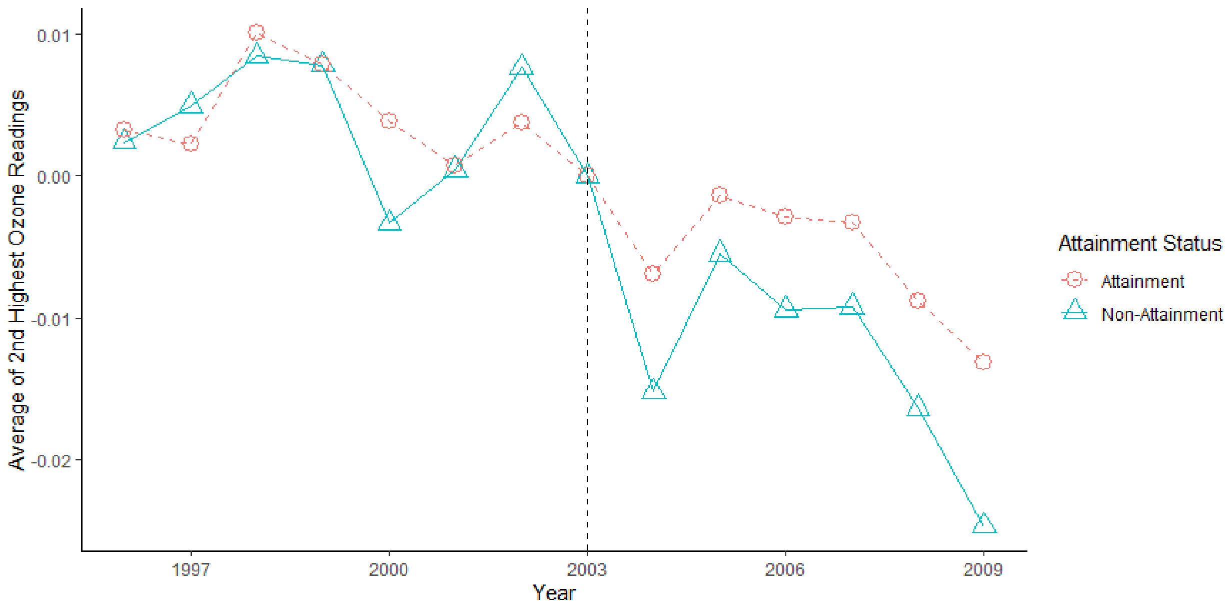
In this paper, I first discuss the decision to take sick leave by workers, and how this decision is impacted if a worker has paid sick leave. I show that estimates of productivity gains could be biased upwards if only illness hazard rates are used. I then estimate the impact of the 2004 CAAA ozone regulations on missed workdays. I do this by specifying a Difference-in-Difference model, which estimates the causal impact of the policy by comparing a treatment group to a control group. Since the CAAA only affected certain counties that had historically high levels of pollution, I identify the treated group by location. I find that the Clean Air Act Amendment reduced the probability of missing work due to illness by about 0.1 percentage points.

3.2 Clean Air Act Amendment of 2004

The policy I consider is the Clean Air Act Amendment of 2004. These amendments updated the National Ambient Air Quality Standards (NAAQS) for ozone and PM2.5 (particulate matter) concentrations. The policy was first proposed in 1997, and, after several years in court, was enacted in 2003 and began enforcement in summer of 2004. As a result, 436 counties were designated as "nonattainment" for not meeting ozone concentration standards. States with nonattainment areas were then required to submit a State Implementation Plan (SIP) which details how governments will reduce ambient pollutant concentrations. The plans were due back to the EPA in 2004, which was when states began implementing restrictions on air pollution.

In this paper, I focus on ozone concentration which is known to be harmful to respiratory health. I am currently working on mapping PM 2.5 counties as well, and there is likely a large overlap. The comparison of these pollutants is important, and it could provide a useful second source of variation. For now, the empirical portion of this paper only includes nonattainment areas for ozone concentration. Figure 3.1 shows the effect of the NAAQS on ozone pollution using data from the EPA. This figure shows the average of the second highest daily one-hour ozone reading in attainment and non-attainment counties in each year. The underlying data has an observation for each county using and each year, yielding 13,255 observations. I then take the simple average by attainment status and plot this statistic over the years 1996-2009. Counties in the control group who retained attainment status are shown by the broken red line and circle points. Counties in the treatment group that were classified as non-attainment are shown in blue solid line with triangle points. All points are shown relative to the first pre-treatment year 2003. The figure shows that ozone levels were trending downward in general during the total sample period. However, after the implementation of the NAAQS in 2003, the non-attainment counties decrease ozone by a greater amount than counties that were designated attainment status. It is important to note that these statistics do not consider strategic monitor placement. If non-attainment counties simply moved monitors to cleaner areas or only operated them on low pollution days, these results will be biased. Using satellite imagery to measure air pollution may be a possible solution to this, but the images needed to make these datasets may not be available for the early 2000s.

Figure 3.1: Average of 2nd Highest Ozone Readings in Attainment vs. Non-Attainment Counties



Notes: This figure shows the average of the 2nd highest reading across all counties in the attainment area. The 2nd highest reading of ozone in a county is an index of ozone pollution produced by the EPA. For each year, observations for each county and year are obtained from the EPA air quality index annual records. I then group all counties as Attainment and Non-Attainment and take a simple average across them to produce the point estimates in each year. The vertical dashed line at 2003 indicates the last pre-period year.

3.2.a Hazard Rate for Illness and Sick Days

In this paper by "sick days," I am referring to short term leave due to temporary illness. I am not considering long term illness that may push somebody out of the labor market for an extended period.

An increase in the labor supply (decrease in sick days) is often put into the benefits column when judging environmental policy. The argument is clear: less pollution means less sick time and more production. So even if policy makers were only using gross domestic product or some similar measure as a goal, there would still be a reason to enact pollution regulation. For example, lost productivity (LP) might be expressed as the number of sick days taken in a year such as the following.

$$LP = \theta(q) \times wage \times 260$$

Where $\theta(q)$ is the probability of getting sick given some level of environmental quality q. So, the gain in productivity (reduction in lost productivity) would be

$$Gain = -\frac{\partial LP}{\partial q} = -\frac{\partial \theta}{\partial q} \times wage \times 260$$

$$and \qquad \frac{\partial \theta}{\partial q} < 0$$

One problem researchers have noted is that this measure does not include the possibility of averting or mitigating behavior. So, assuming the probability of taking a sick day is $s(\theta)$ a more proper measure of a gain in productivity might be

$$Gain = -\frac{\partial s}{\partial \theta} \times \frac{\partial \theta}{\partial q} \times wage \times 260$$

The new term on the right-hand side reflects the possibility of attending work while sick or other mitigating behavior. If researchers simply use the first equation, then they implicitly assume $\frac{\partial s}{\partial \theta} = 1$ and the results will be biased upward. However, even if researchers account for mitigation, results may be biased upward if some workers have unpaid sick leave. Workers may strategically go to work sick and save their banked sick day. This choice means that even if the government policy lowers the probability of getting sick, the presence of paid sick leave may reduce the number of people who attend work while sick. If the government can credibly commit to the policy, then the probability of getting sick is lower, but it is also lower in the future. Since part of the opportunity cost of taking a sick day today is the inability to take a sick day tomorrow, a lower probability of getting sick tomorrow means a lower opportunity cost to taking a sick day today. A simple model of paid sick leave and pollution is presented in Appendix C. While this is an interesting avenue of research, due to data limitations, this paper does not include empirical estimates of this effect.

3.3 Data and Empirical Strategy

I use the current population survey (CPS) basic monthly questionnaire to create the sample to estimate my model. Summary statistics are presented in Table 3.1, where all observations are separated by attainment status. Table 3.2 the same except the sample is restricted to only employed persons. Using geographic variables, I can identify whether a household was in a non-attainment area. I use demographics to create a vector of person-specific variables. Survey respondents indicate how many hours each household member worked last week. They also report how many hours each household member usually works per week. If somebody worked part-time in the previous week, they also note why they worked part-time or

Table 3.1: Summary Statistics for All Observations

Attainment					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Employed	6,561,067	0.65	0.48	0	1
Hourly Wage	556,757	13.49	7.23	5.15	99.5
Hours Worked	3,820,211	40.63	11.76	0	120
Age	6,561,067	47.51	16.88	20	90
Female	6,561,067	0.52	0.50	0	1
White	6,561,067	0.87	0.34	0	1
Married	6,561,067	0.61	0.49	0	1
High School	6,561,067	0.53	0.50	0	1
College	6,561,067	0.34	0.47	0	1

Non-Attainment					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Employed	2,778,904	0.65	0.48	0	1
Hourly Wage	214,927	14.25	8.26	5.15	99.5
Hours Worked	1,657,315	40.53	10.92	0	120
Age	2,778,904	46.43	16.64	20	90
Female	2,778,904	0.53	0.50	0	1
White	2,778,904	0.79	0.41	0	1
Married	2,778,904	0.57	0.49	0	1
High School	2,778,904	0.48	0.50	0	1
College	2,778,904	0.38	0.48	0	1

Notes: This table presents summary statistics for observations in attainment and non-attainment counties. The top panel shows the mean, standard deviation, minimum, and maximum for each variable. All observations are included, however only observations recorded on the supplemental survey in March include hourly wages. Hours worked are listed in the CPS data as “usual hours worked”. The maximum hourly wage is $99.5 per hour and the maximum hours worked per week is 120.

Table 3.2: Summary Statistics for Sample Restricted to Employed Individuals

		Attainment			
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Employed	4,247,386	1	0	1	1
Hourly Wage	556,475	13.49	7.23	5.15	99.5
Hours Worked	3,816,402	40.67	11.70	1	120
Age	4,247,386	42.27	12.77	20	90
Female	4,247,386	0.48	0.50	0	1
White	4,247,386	0.87	0.33	0	1
Married	4,247,386	0.63	0.48	0	1
High School	4,247,386	0.52	0.50	0	1
College	4,247,386	0.39	0.49	0	1
		Non-Attainment			
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Employed	1,807,804	1	0	1	1
Hourly Wage	214,830	14.25	8.26	5.15	99.5
Hours Worked	1,656,058	40.56	10.86	1	120
Age	1,807,804	41.66	12.54	20	90
Female	1,807,804	0.47	0.50	0	1
White	1,807,804	0.80	0.40	0	1
Married	1,807,804	0.59	0.49	0	1
High School	1,807,804	0.46	0.50	0	1
College	1,807,804	0.44	0.50	0	1

Notes: This table presents summary statistics for observations in attainment and non-attainment counties. The top panel shows the mean, standard deviation, minimum, and maximum for each variable. Only observations that report some form of employment are included, however only observations recorded on the supplemental survey in March include hourly wages. Hours worked are listed in the CPS data as “usual hours worked”. The maximum hourly wage is $99.5 per hour and the maximum hours worked per week is 120.

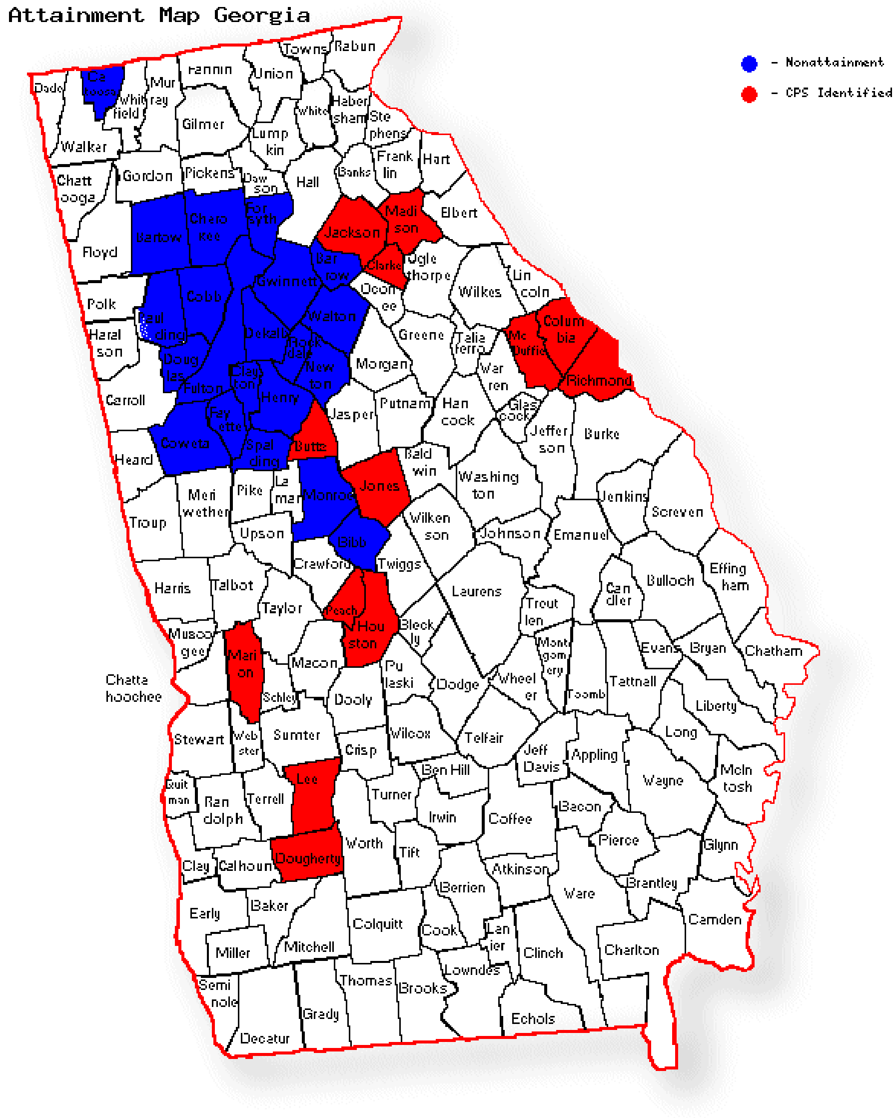
were absent from work. These two variables allow me to observe hours missed due to illness for a national sample.

There are two primary issues with the data. The first is matching the geography to households. The CPS censors some of this information for privacy concerns, which can lead to some issues. The primary problem is that geographic variables do not exactly line up to regulation boundaries. The Current Population Survey does not report counties for all observations to maintain privacy. Instead, data on county or metropolitan area are indicated depending on the size of the county or metro area. However, since most non-attainment areas were urban, it is possible to identify most non-attainment areas. Using a combination of county and metropolitan areas I create a mapping of CPS observations to non-attainment and attainment areas. Using this matching strategy, I end up with some overlap between areas. So, some households that are in non-attainment areas may be mislabeled as being in an attainment area and vice-versa. Counties that are not identified in the CPS represent less than 7% of the regulated counties.

Tying a concentration of ozone to locations identified is difficult for two reasons. The first is because the household may simply be part of a larger metropolitan area. Suppose I have a single state such as Georgia which has some counties that switched to non-attainment status because of the CAAA. The map in Figure 3.2 shows the non-attainment areas in blue and other attainment areas identified by the CPS in red. The CPS identifies some of the non-attainment counties directly, and some are included in larger metropolitan areas such as the Atlanta area. So, it is possible that some entire metro areas are identified as non-attainment even though they contain some counties identified as attainment. So, it is unclear how to assign pollution monitors since there will likely be several in a large metro area. Additionally, if a person is not in a non-attainment (blue filled) area, then I know they are in Georgia and not in a regulated county. This means they are somewhere in the white area, but I cannot tell where so assigning a pollution monitor is even more difficult. One possibility is using an average weighted by population measured by the ACS. This will assign a state-wide average pollution level for attainment counties, so it is unclear how closely this matches local conditions.

The second major limitation of the data is the lack of an hourly wage variable. The CPS only asks detailed information about earnings for the outgoing rotation groups, so including an hourly wage measure cuts the sample by 90%. However, I may be able to overcome this with my difference in difference approach. While wages were higher in the non-attainment areas, we need to compare the difference in changes over time. For the sample that I have, the change in wages was largely the same between the two attainment and nonattainment areas. However, wages in the non-attainment areas fell slightly during the regulation period relative to the attainment areas. I show the change in wages relative to 2003 in Figure 3.3. My simple model of sick leave in the previous section predicts that, in general, workers are less likely to miss work as wages increase. Although, the effect could go the other way if higher wages mean more access to sick leave benefits. Keeping this in mind I now turn to the model using the full sample and dropping hourly wages from my analysis.

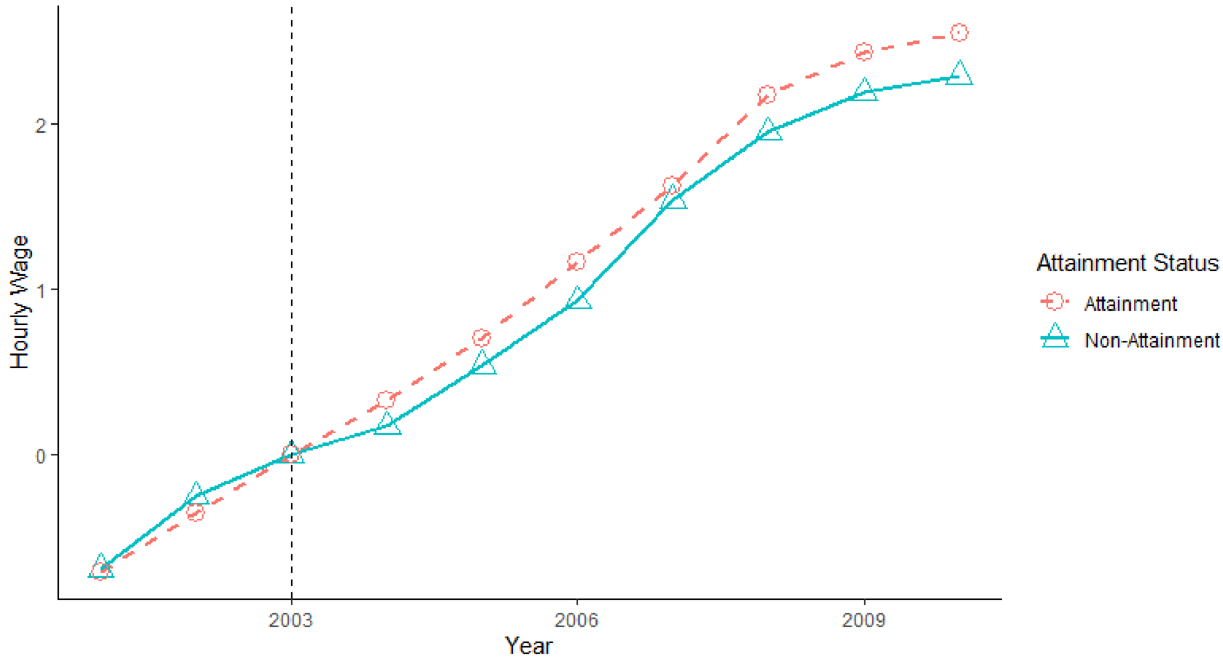
Figure 3.2: Map of Attainment, Non-Attainment, and CPS Identified Areas in Georgia



Source: diymaps.net (c)

Notes: This figure shows attainment and non-attainment counties in Georgia, along with the counties that are identified by the CPS. Blue counties were designated as non-attainment counties by the 2004 CAAA ozone regulations. All blue counties are identified in the CPS. Red counties were designated attainment counties and are also identified in the CPS data. White counties are attainment counties that are not identified in the CPS data due to censoring of low-population areas. This map was created using software from www.diymaps.net.

Figure 3.3: Hourly Wages Over Time



Notes: This graph shows the hourly wage relative to 2003 (vertical axis) over the years in the sample period (horizontal axis). The dashed line with red circle points represents the areas designated as attainment, and the blue solid line with triangle points represents the hourly wage in non-attainment areas. The vertical dashed line at 2003 indicates the last pre-period year.

3.3.a Model Description

I study the impact of the CAAA on lost workdays using a difference-in-difference (DiD) model. Using data from states with at least one non-attainment area I compare households that lived in a non-attainment area and those that lived in an attainment area. The assumption is that areas that were designated non-attainment saw a decline in pollutants regulated under the CAAA. I use this variation to identify the effect of air pollution regulation on sick leave. I define the following econometric model:

$$Y_i = \beta_0 + \beta_1 NonAttain_i + \beta_2 Post_i + \beta_3 NonAttain_i \times Post_i + State_i + Month_i + \boldsymbol{X_i} + \mu_i$$

The above equation is the central research question for this paper. The outcome variable is a binary variable indicated whether or not person i took at least one day of leave in the reference week. The reason for leave can vary for the specification. In the main analysis, I include whether or not the person took leave giving the reason "sick leave," but I also include specifications where the worker took leave for other given reasons, such as vacation. *NonAttain* is a binary variable equal to 1 if the respondent is in a non-attainment area, and *Post* is equal to 1 if the observation is after 2003. The coefficient on the interaction of these two variables is the result of interest. Variables $State$ and $Month$ are state and month fixed effects. I use state fixed effects to account for unobserved heterogeneity by location. Month fixed effects are included to account for unobserved heterogeneity over the year, since sick days are clearly correlated with seasons. The variable μ is an idiosyncratic disturbance term assumed to be distributed normally with mean zero. The matrix $\boldsymbol{X}$ is a collection of demographic variables: age, sex, marital status, race, education, and usual hours worked.

This method is like that used by Walker (2013), whereas Greenstone and Chay (2003) use an instrumental variable (IV) approach. Using an IV approach is appealing because it gives the marginal effect of pollution concentration changes on outcome variables. Greenstone and Chay utilize datasets with fine geographic detail, which allows them to use attainment status to instrument a local pollution level. Due to the nature of CPS data restrictions, this may be unfeasible for this study. As I discussed before, given that a person is in an attainment area, I am, in many cases, unable to determine which county they are in. Therefore, I am unable to reliably assign a specific pollution concentration monitor to households in attainment areas. Additionally, it is not clear which pollution measure to use. For Greenstone and Chay, they investigate Total Suspended Particles (TSP), and simply use an average concentration level. For ground level

Ozone, however, temperature and time of day are important determinants of the impact of this pollutant. I leave these questions for future research, and instead focus on the estimates from my DiD design.

3.4 Results

Table 3.3 provides the raw DiD results from the data using no controls. The data is divided into four samples, attainment areas before and after 2003 and non-attainment areas before and after 2003. The percent of workers who reported they worked part-time last week because of illness or other health limitations are reported in each cell. The columns are observations for before and after the treatment period (regulation began in 2004) and the rows are observations in attainment and nonattainment areas. The first difference is the difference over time which is shown in the third column. The difference between attainment and nonattainment areas is the second difference, which is reported in the third row. The difference between these numbers is the raw DiD estimate. This indicates that the Clean Air Act reduced the probability of missing work due to illness by about 0.14 percentage points.

Table 3.3: Difference-in-Difference for Probability of Missing Work Due to Illness

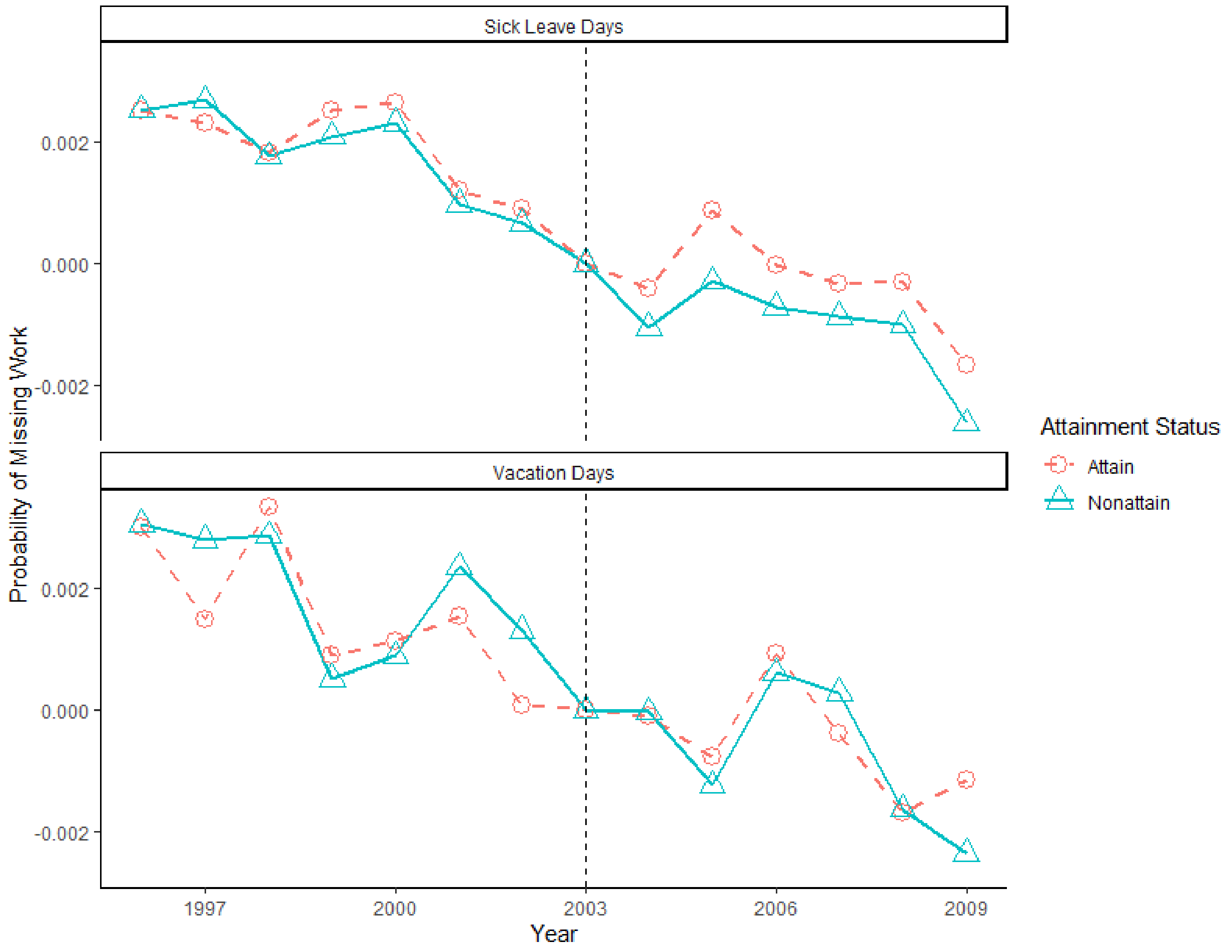
	Pre-2003	**Post-2003**	**Time Diff.**
Attainment	2.72	2.33	-0.39
Nonattainment	2.34	1.81	-0.53
Group Diff.	-0.38	-0.52	**-0.14**

Notes: This table shows the uncontrolled DiD estimate for the effect of the 2004 CAAA ozone restrictions on missed work. The elements inside the borders are each the percent of workers that indicated that they missed at least one day of work in the previous week due to illness. The far right column shows the difference before and after the treatment period, and the bottom row shows the difference between groups in both periods. The difference between these differences is the raw DiD estimate, which is bolded in the bottom right corner.

Figure 3.4 also shows the raw DiD estimate by year. For each panel in Figure 3.4, the horizontal axis is the year and the vertical axis reports the percent of people who reported they missed work in the reference week. Note that this percentage is expressed relative to 2003 such that the value in 2003 is zero. The top panel of this figure uses work missed for the given reason that the respondent was sick. The first interesting observation about both graphs is that the probability of missing work for either reason seems to have generally trended down during the sample period. However, the top panel shows that after 2003, non-attainment areas saw a bigger decrease in the probability of taking a sick day than workers in attainment areas. Additionally, this effect seems to be absent in the bottom panel, which shows the same calculation using missed work where the stated reason was vacation time. The bottom panel is something of a placebo test but not quite. An initial reaction may be that vacation days should not be correlated with a reduction in pollution. However, workers may take vacations to get away from polluted areas, so a reduction in pollution may reduce mitigating behavior. However, it seems from this figure that this is not the case.

In Table 3.4, I present the results from the full DiD regression. The outcome variable is binary, indicating whether the respondent missed work at all in the reference week. From left to right, the columns show the results using different reasons given for missing work. The first column uses all missed days, the second uses missed days because the respondent was sick, and the third uses missed days because the respondent was on vacation. These are linear probability models so coefficients can be interpreted as a percentage point change in the probability of missing work last week. The first column shows the results using all missed days regardless of their classification by the respondent. This could include missed days due to child care, civic duties, illness, and vacation days. The results suggest that the policy lowered the probability of missing work for any reason by about .5 percentage points. The result for only sick days is reported in the second column. Here the coefficient is smaller but still statistically significant.

Figure 3.4: Event Study for DiD Results



Notes: This graph shows the raw DiD estimates for each year over the sample period. The dashed line with red circle points represents the areas designated as attainment, and the blue solid line with triangle points represents the hourly wage in non-attainment areas. The vertical dashed line at 2003 indicates the last pre-period year. The top panel uses only days missed where the respondent indicated that they missed work due to illness. The bottom panel uses only days missed where the respondent indicated that they missed work due to taking vacation time.

Table 3.4: Results for Effect of CAAA on All Missed Days, Sick Days, and Vacation Days

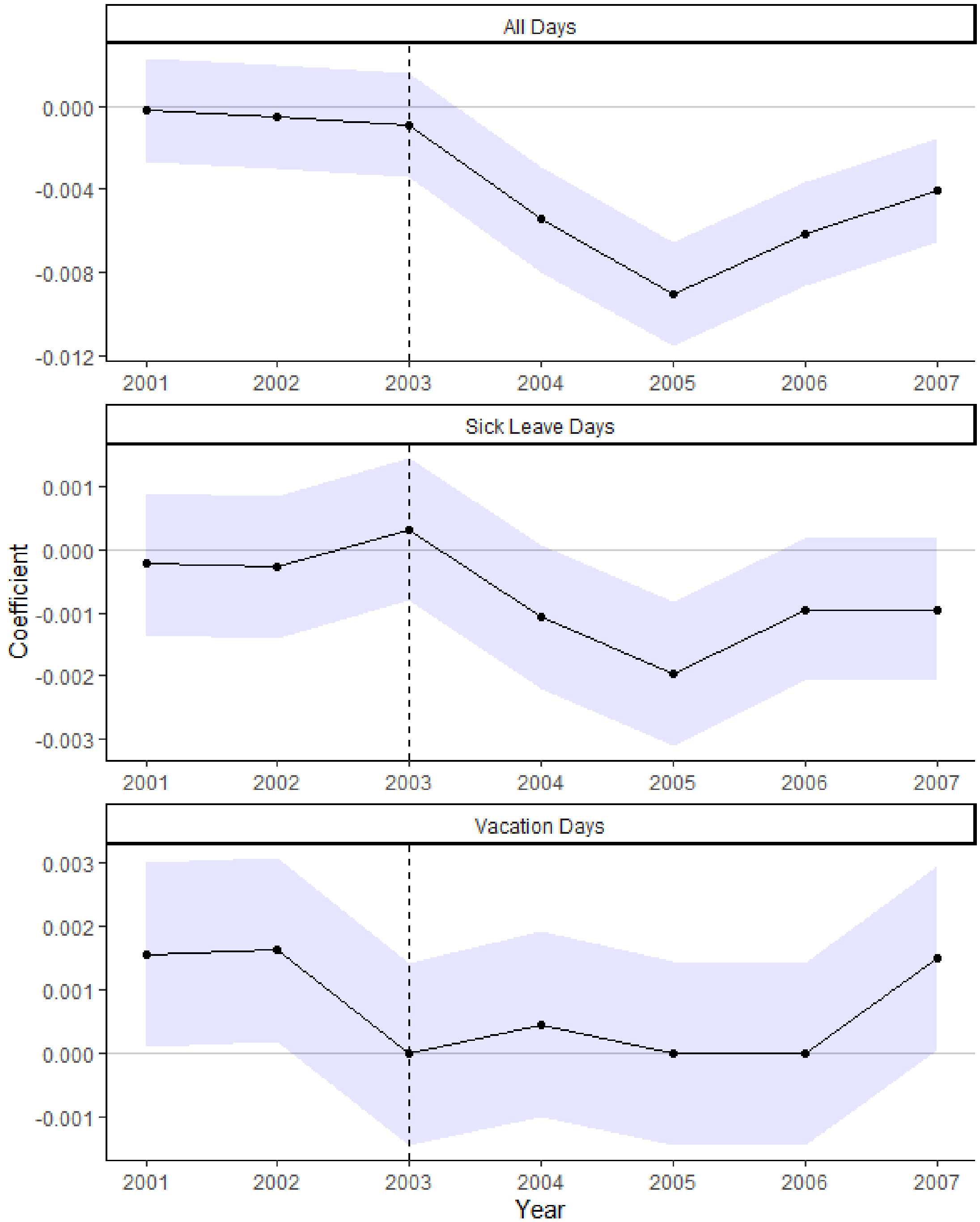
VARIABLES	(1) All Days	(2) Sick Days	(3) Vacation Days
Non-Attainment X Post	-0.00497	-0.00110	-0.00025
	(0.00263)	(0.00053)	(0.00073)
Usual Hours	-0.0193	-0.000922	-6.04e-05
	(0.000268)	(2.54e-05)	(1.27e-05)
Age	0.000956	0.000566	0.000488
	(5.59e-05)	(1.29e-05)	(2.03e-05)
Female	0.0474	0.00566	0.00979
	(0.00177)	(0.000358)	(0.000526)
White	0.0341	-0.00240	0.00873
	(0.00237)	(0.000521)	(0.000577)
Married	0.00233	-0.00930	0.00533
	(0.00150)	(0.000415)	(0.000318)
High School	0.00353	-0.00657	0.0140
	(0.00586)	(0.00187)	(0.000968)
College	0.0150	-0.0144	0.0310
	(0.00727)	(0.00201)	(0.00113)
Non-attainment	-0.00619	-0.00213	-0.000830
	(0.00374)	(0.000995)	(0.00120)
Post	-0.00414	-0.00163	-0.00236
	(0.00140)	(0.000384)	(0.000457)
Observations	5,472,460	5,472,460	5,472,460
R-squared	0.284	0.009	0.016

Notes: This table reports results from a DiD regression. The coefficient of interest is the coefficient on the interaction of variables Non-Attainment X Post. This is the difference in difference treatment effect of the CAAA on the outcome variable. The outcome variable is binary indicating whether the respondent missed work in the reference week. Three types of missed work are used: all days, sick days, and vacation days. Standard errors are reported in parentheses.

These results indicate that the policy reduced the probability of taking a sick day by about .1 percentage points. The final column is the same regression, except I use work missed for the stated reason of vacation time. The last column confirms the visual evidence in Figure 3.4, the coefficient on the treatment effect for vacation days is small and statistically insignificant, indicating that the CAAA had no effect on the probability of taking a vacation day in the reference week.

I now use an event study framework to probe the robustness of the results in the earlier section. Results from this exercise are shown in Figure 3.5. For each of the regressions in the previous section, I interact the difference in attainment status with the year. So, each graph shows the conditional difference between attainment and non-attainment areas for each year in comparison to the year 2000. The black line in the middle blue shaded areas is the coefficient, and the outer shaded areas are the 95% confidence bounds. The top panel shows the change in all missed days. The results of the previous table are confirmed; after 2003 the coefficient becomes statistically significantly negative until it begins to trend upward in 2006. The second panel shows a similar pattern for sick days, except the measure is a bit noisier. In the final years of the sample, the 95% confidence bounds cross the 0 threshold. The last panel shows the event study for vacation days. No clear pattern emerges here, and the estimate simply bounces around zero over the regulation period. There does seem to be a statistically significant rise in vacation time directly at the beginning of the sample for the years 2001 and 2002. However, the coefficients quickly revert back to zero for the rest of the sample period. Again, confirming the results found in Table 3.4 and Figure 3.4.

Figure 3.5: Event Study for DiD Coefficients



Notes: This figure shows the regression results from interacting the difference in attainment status with each year in my sample period. 2000 is dropped and used as the reference year. The top panel uses work missed for any reason, the second panel uses work missed due to illness, and the third panel uses work missed for vacation time. The black line and points are the estimated coefficients and the blue shaded areas show the 95% confidence bands. The vertical dashed line at 2003 indicates the last pre-period year.

Lastly, I also consider some other specifications of my econometric model. In Table 3.5, I remove month fixed effects and add year fixed effects. The results are largely the same across all specifications. The coefficient on the interaction term is slightly smaller for column 3, but this has the most restrictions, so I am losing a lot of variation between groups. Additionally, the r-squared remains quite small, so I am likely not gaining much explanatory power from adding in year fixed effects. The final regression results I show are for the sample including hourly wages. The results of regressions including hourly wages are reported in Table 3.6. The estimates of the interaction effect on all days and sick days are smaller, but they are going the same direction as in Table 3.4. These estimates are much noisier due to having to drop most of the sample to account for missing wages. Additionally, the CPS includes the supplemental questions on earnings only in March. However, ground level ozone is often created with volatile compounds combine in hot weather. This makes summer months the most likely times when ozone would cause respiratory problems. Due to these issues, it is unlikely that I would be able to pick up effects using only observations during the month of March.

From my preferred specifications, my estimates predict that the probability of missing work was reduced by about 0.1 percentage points due to the CAAA 2004 Ozone restrictions. According to CPS data, counties that switched attainment status covered about 30% of the population in the United States. Since workers missed one day when they did miss work in a given week, a 0.1 percentage point increase is an decrease of about 2 million sick days. Using an average daily wage of $114, the benefits from decreased sick leave is approximately $248 million. In their second prospective of the benefits of the CAAA, the EPA estimated that the PM 2.5 and Ozone restrictions of the CAAA decreased sick days by about 13 million in 2010. This is larger than my estimate, however, it includes all previous Ozone restrictions as well as PM 2.5

Table 3.5: Sensitivity Analysis

	(1) Sick Days	(2) Sick Days	(3) Sick Days
NonAttain X Post	-0.00110	-0.00116	-0.00103
	(0.000533)	(0.000537)	(0.000528)
Usual Hours	-0.000922	-0.000925	-0.000924
	(2.54e-05)	(2.56e-05)	(2.54e-05)
Age	0.000566	0.000566	0.000568
	(1.29e-05)	(1.29e-05)	(1.29e-05)
White	-0.00240	-0.00238	-0.00243
	(0.000521)	(0.000521)	(0.000521)
Female	0.00566	0.00568	0.00564
	(0.000358)	(0.000358)	(0.000358)
Married	-0.00930	-0.00926	-0.00932
	(0.000415)	(0.000412)	(0.000416)
HS	-0.00657	-0.00654	-0.00656
	(0.00187)	(0.00188)	(0.00187)
CO	-0.0144	-0.0144	-0.0144
	(0.00201)	(0.00201)	(0.00201)
NonAttain	-0.00213	-0.00207	-0.00221
	(0.000995)	(0.000999)	(0.000985)
Post	-0.00163	-0.00163	-0.00492
	(0.000384)	(0.000383)	(0.000498)
Year Fixed Effects			X
Month Fixed Effects	X		X
Constant	0.0638	0.0584	0.0664
	(0.00321)	(0.00305)	(0.00320)
Observations	5,472,460	5,472,460	5,472,460
R-squared	0.009	0.009	0.009

Notes: This table reports results from a DiD regression. The coefficient of interest is the coefficient on the interaction of variables Non-Attainment X Post. This is the difference in difference treatment effect of the CAAA on the outcome variable. The outcome variable is binary indicating whether the respondent missed work in the reference week. For this table I considered other specifications including year and month fixed effects.

Table 3.6: Regressions Including Hourly Wage

VARIABLES	(1) All Days	(2) Sick Days	(3) Vacation Days
NonAttain X Post	-0.00310	-0.000188	0.000642
	(0.00184)	(0.000932)	(0.00101)
Usual Hours	-0.0263	-0.000945	8.64e-05
	(4.51e-05)	(2.28e-05)	(2.48e-05)
Hourly Wage	-0.000831	-0.000126	0.00104
	(6.26e-05)	(3.16e-05)	(3.43e-05)
Age	0.000518	0.000776	0.000509
	(3.45e-05)	(1.74e-05)	(1.89e-05)
Female	0.0438	0.00603	0.00803
	(0.000879)	(0.000444)	(0.000483)
White	0.0255	-0.00116	0.00598
	(0.00110)	(0.000555)	(0.000604)
Married	-0.00114	-0.00977	0.00321
	(0.000885)	(0.000447)	(0.000486)
High School	0.0135	-0.00393	0.0109
	(0.00128)	(0.000649)	(0.000706)
College	0.0287	-0.0104	0.0171
	(0.00150)	(0.000760)	(0.000826)
NonAttain	-0.00317	-0.00183	-0.00129
	(0.00135)	(0.000682)	(0.000741)
Post	-0.00252	-0.00227	-0.00397
	(0.00179)	(0.000535)	(0.000582)
Constant	1.178	0.0609	-0.0383
	(0.00469)	(0.00231)	(0.00251)
Observations	715,894	715,894	715,894
R-squared	0.355	0.008	0.013

Notes: This table reports results from a DiD regression. The coefficient of interest is the coefficient on the interaction of variables Non-Attainment X Post. This is the difference in difference treatment effect of the CAAA on the outcome variable. The outcome variable is binary indicating whether the respondent missed work in the reference week. These regressions are the same as Table 3.4, except I include the hourly wage. This is only included for the sample answering questions in March, however, so it drops a great deal of the sample.

restrictions. Given that restrictions in 1990 were likely larger and particulate matter may have larger heath effects, I would argue that my results support the EPA estimates of lost work days from air pollution.

3.4.a Further Research

I am currently focused on three main objectives for future research. The first is including the PM 2.5 non-attainment counties. Using this policy could help improve my estimates as it provides more policy variation. The second area of continued research is using an instrumental variables approach to get point estimates based on some measure of pollution. This may require more detailed survey data if pollution maps poorly to the data. I will also likely need to use several measures of Ozone, since it is unclear which is most hazardous for human health. The third area of continued research is attempting to include hourly wages in the model. It may be possible to increase my sample size by increasing the number of years. However, this means that I would have to include years from the Great Recession, which has confounding effects. This might be able to be mitigated by using CPS datasets that match observations across surveys. If I assume that a person's wage does not change over the year, then I can simply assign the wage observed each March to all other observations for that person.

3.5 Conclusion

There are many potential gains to studying missed work and environmental quality. In this paper, I have explored the choice a worker faces when deciding whether to take a sick day. This is important because it can affect how we measure productivity gains from environmental regulation. Less sick leave time is often included in government benefits analysis for pollution control policies; however, it has not been studied in the causal literature. This effect is effect is a broader benefit, in that the individual benefits are small, but it effects many more people. Mortality effects, for example, are a narrow benefit in that it only affects a few people, but the individual benefits are large.

My results indicate that there is some effect from the CAAA on sick leave from work, confirming earlier work on pollution and missed work. I find that the CAAA ozone regulations of 2004 reduced the probability of taking a sick day by 0.1 percentage points. This indicates that there is some productivity to be gained from environmental regulation. According to the BLS, there were 139 million employed person in the US in 2004. Using my DiD estimate and the fact that on average workers missed one day in the previous week when they missed work, the CAAA decreased sick leave by 3 million days in 2004.

I can also use the estimates from this study to evaluate the predictive ability of the EPA's simulation model. The effect I measure in this paper is just from one regulation of the CAAA. If previous actions had similar effects, then the EPA's estimate of 17 million fewer sick leave days seems reasonable. Evaluating the simulation methods used to determine policy impacts is a necessary endeavor. Computational models are important influences on policy, and researchers should evaluate how well they perform in predicting policy effects. Using causal empirical techniques can provide a good framework for doing so.

Appendix A: Data and Calibration

I use data from the World Input-Output Database to calibrate the model. This data includes 35 industries, which I aggregate to 15 industries. The WIOD also includes emission data and energy use by industry, so I can also calibrate emissions. In this section, I first detail how I aggregate or disaggregate the industries and create the input-output tables used to calibrate the economic portions of the model. I then detail how I connect data on emissions to the economic data.

The first task is to create a worldwide input-output table. This is a matrix that shows the circular flow of goods in an economy. Each row represents an input to the industry listed in the column. To start, I use the 2011 World Input-Output Table, which represents 35 industries across 40 countries. All other countries are included in a final region termed "rest of the world," so the data represents a balanced input-output matrix for the whole world. The 35 original industries are listed in Table A.1. A code is provided for each industry; those that start with "c" are the original industries from the WIOD that I start with. The industries with codes that start with "a" are the added fossil fuel industries. The goal of the process outlined here is to create a balanced input-output matrix with these three fossil fuel industries separated from the mining industry.

To capture emissions accurately, I need to separate the fossil fuel extraction industries from the rest of the mining industry. I first disaggregate the "Mining and Quarrying" industry, which contains the extraction of fossil fuels and all other mined resources. I can do this using a "use table," which is available for each country in my data from WIOD. The use table reports how much of each commodity an industry uses in production. The use tables in the WIOD report much more detailed subcategories for the mining industry, which are listed in Table A.2. For each industry, I find the amount of each commodity input as a share of the total mining inputs.

Table A.1: Industry Aggregation

Code	Detail Name	Agg. Industry
a1	Coal Mining	Coal Extraction
a2	Oil Extraction	Oil Extraction
a3	Gas extraction	Natural Gas Extraction
c1	Agriculture, Hunting, Forestry and Fishing	Agriculture
c2	Mining and Quarrying	Mining
c3	Food, Beverages and Tobacco	Goods Manufacturing
c4	Textiles and Textile Products	Goods Manufacturing
c5	Leather, Leather and Footwear	Goods Manufacturing
c6	Wood and Products of Wood and Cork	Goods Manufacturing
c7	Pulp, Paper, Paper , Printing and Publishing	Goods Manufacturing
c8	Coke, Refined Petroleum and Nuclear Fuel	Petroleum Refining
c9	Chemicals and Chemical Products	Chemical Manufacturing
c10	Rubber and Plastics	Chemical Manufacturing
c11	Other Non-Metallic Mineral	Chemical Manufacturing
c12	Basic Metals and Fabricated Metal	Other Manufacturing
c13	Machinery, Nec	Other Manufacturing
c14	Electrical and Optical Equipment	Other Manufacturing
c15	Transport Equipment	Other Manufacturing
c16	Manufacturing, Nec; Recycling	Other Manufacturing
c17	Electricity, Gas and Water Supply	Utilities
c18	Construction	Construction
c19	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles	Consumer Services
c20	Wholesale Trade and Commission Trade, Except of Motor Vehicles	Consumer Services
c21	Retail Trade, Except of Motor Vehicles; Household Repair	Consumer Services
c22	Hotels and Restaurants	Consumer Services
c23	Inland Transport	Transportation

c24	Water Transport	Transportation
c25	Air Transport	Transportation
c26	Other Supporting and Auxiliary Transport Activities	Transportation
c27	Post and Telecommunications	Business Services
c28	Financial Intermediation	Business Services
c29	Real Estate Activities	Business Services
c30	Renting of Equipment and Other Business Activities	Business Services
c31	Public Admin and Defence; Compulsory Social Security	Social Services
c32	Education	Social Services
c33	Health and Social Work	Social Services
c34	Other Community, Social and Personal Services	Social Services
c35	Private Households with Employed Persons	Social Services

Table A.2: Sub-Components of Mining Industry

Coal and lignite; peat
Crude petroleum and natural gas
Uranium and thorium ores
Metal ores
Other mining and quarrying products

To give a concrete example, we can look at the US's non-metallic manufacturing industry. This industry uses $20.5 billion worth of mining inputs. The use table tells us that 32% of mining inputs are coal, and the rest are metal ores. So, for the non-metallic industry in the US, I assign 32% of mining inputs as coal and the rest as other mining. Using this method, I split inputs for each industry into coal, oil and gas extraction, and other mining. For the "rest of the world" region, I use the average shares from all other countries. Once each mining industry is split, I have essentially created two more industries: coal mining and oil and gas extraction. Now, I turn to separating natural gas and crude oil.

The use tables can define coal mining and oil and gas extraction, but this is as detailed as the tables get. So, to separate natural gas from crude oil, I must use the energy use accounts. The energy use tables are included with WIOD and matched to world input-output tables. The tables show fuel use by each industry for every country in the dataset. Fuel use is quoted in joules, so I need to convert these quantities to the units in the input-output matrix, dollars. To do this, I create a ratio of prices for oil and natural gas per joule. I use data from the Energy Information Agency (EIA) in the US and the International Energy Agency (IEA) in France. These agencies give price indices for natural gas and crude oil in standard units. To find a price per joule, I first calculate average worldwide prices for natural gas and oil in their respective units. For natural gas, the price is about $3.40 per million British thermal unit (Btu), and for oil the price is $102 per barrel. Using the energy conversion calculators from the EIA, a barrel of oil contains about 6 times as many joules as a Btu of natural gas. Using this, we get that crude oil is about 4.9 times more expensive than natural gas per joule.

After getting the price ratio, I can then estimate input volumes for oil and natural gas separately. This process is like the previous separation of coal and oil and gas extraction. For each industry, I multiply the joules of crude oil used in production by my price ratio, 4.9, and take the corresponding shares. So, if an industry in the US used 3,000 Terajoules of crude oil and 5,000 Terajoules of natural gas, then I would estimate 75% of their oil and gas extraction inputs were crude oil. So, if this spends $20 billion on oil and gas extraction inputs, I would estimate $15 billion was spent on crude oil and the rest spent on natural gas. This process needs to then be done for every industry in every country.

Here it is important to note that most crude oil is only used by one industry: petroleum refining. This makes sense as oil is not really useful until it is refined into a stable petroleum product. Additionally, the major buyer of natural gas is the electricity and utilities industry. This essentially means that the price ratio is not a strong determinant of the final data. When I use other price ratios to check the robustness of the procedure, I get a very similar input-output matrix. Using the final data and an average price per barrel of $100, my estimates indicate that the US consumed 17.4 million barrels of oil per day in 2011. This is close to the estimate from the EIA of 18.8 million barrels per day.

At this point, I have separated the rows of the input-output matrix, and now I need to construct the columns. To disaggregate the columns of the IO matrix, I would need disaggregated production data for each of the fossil fuel extraction industries. The energy use tables show how much of each fossil fuel is used by each industry. WIOD does not show how much of each industry output is used by each fossil fuel industry. Recall that this is all aggregated in the "mining" industry in the original data. To separate the columns of the input-output matrix, I sum the elements of each row to get the total output for each fossil fuel industry. I then use the shares of total output to disaggregate the columns. This makes the assumption that production processes are similar between mining industries.

This process yields a balanced input-output matrix that includes fossil fuel industries. This can then be linked to emission data to calibrate the environmental portion of the model. A visual overview of a simple example is shown in Figure A.1. This figure shows a fabricated input-output matrix for one country with two industries: agriculture and mining. The mining industry is then disaggregated into 3 fossil fuel industries and 1 mining industry.

Figure A.1: Example Energy Decomposition of Input-Output Matrix

Step 1: Original input-output matrix

	Agr	Mine	FD	TO
Agr	30.0	5.0	50.0	85.0
Mine	10.0	20.0	5.0	35.0
VA	45.0	10.0		
TO	85.0	35.0		

Step 2: Separate rows using use and energy tables from WIOD

	Agr	Mine		FD	TO
Agr	30.0	5.0		50.0	85.0
Coal	2.0	2.0		0.0	4.0
Oil	1.0	3.0		0.0	4.0
Gas	2.0	5.0		0.0	7.0
Mine	5.0	10.0		5.0	20.0
VA	45.0	10.0			
TO	85.0	35.0			

Step 3: Separate columns using the shares from total output (TO) column from step 2.

	Agr	Coal	Oil	Gas	Mine	FD	TO
Agr	30.0	0.6	0.6	1.0	2.9	50.0	85.0
Coal	2.0	0.2	0.2	0.4	1.1	0.0	4.0

A.1 Region and Industry Aggregation

I now have a balanced input-output matrix for the world economy that includes fossil fuels. Table A1 shows the 35 original industries plus the 3 added fossil fuel industries, for a total of 38 industries. I now aggregate some of the other 35 industries to create 12 broad economic industries and 3 fossil fuel industries. The final aggregated group for each industry is listed in the third column of Table A.1. Aggregation at this point is simple; for each new industry, the rows and columns are summed to create a new element for the matrix. For example, to create he "Chemical Manufacturing" industry, I sum the rows for industries c9, c10, and c11 to create one row for the new aggregated industry group. I then sum the columns for c9, c10, and c11 to create a new column.

This process creates a new 15 industry input-output matrix for the world. From the 40 countries in the WIOD, I aggregate them into 2 countries and three regions. The first two countries are the United States (US) and China. The three regions are North America, Europe, and the Rest of the World. The North America region is the combination of Canada and Mexico, since these are big trading partners for the US. The second region, Europe, is a combination of the countries in my data that are a European Union member. The final region, Rest of the World, is a combination of all the countries left and the world component of the original WIOD matrix. Each country and its associated group are listed in Table A.3. The second column shows the name of the country, and the third column shows the region. To create the final dataset, I sum all the columns and rows by industry across all countries in a region. So, the column for a given industry in the Europe region would be the sum of the columns for that industry across all countries in the Europe region.

A.2 Calibration Process

Once the data sources are correctly aggregated, a balanced SAM is produced. This gives the values of inputs and outputs for each industry as well as final demand for goods and factors.

To calibrate the model, I adopt a common strategy of choosing parameters from the literature and solving for the other parameters to match my SAM. To do this, I assume the SAM economy is in equilibrium with each price equal to unity.

For the production nests, I first choose the substitution elasticity σ_h and I use the input shares to create the alpha parameters for the CES equation. Define $\hat{X}_{ni}^{j}$ as the share of input i in the production process of firm j in region n. The share parameters are calibrated as $\hat{X}_{ni}^{j\,\frac{1}{\sigma^h}}$. Once these are set, I set prices to unity and solve for the gamma parameter in equilibrium using an arbitrary good k such that $\hat{X}_{nk}^{j} > 0$.

$$\gamma_{nh}^{j} = \left(\frac{\hat{X}_{nk}^{j} \left(\sum_{i=1}^{H} \alpha_{ni}^{j\ \sigma_h} \right)^{\frac{-\sigma_h}{1-\sigma_h}}}{\alpha_{nk}^{j}} \right)^{\frac{1-\sigma_h}{\sigma_h}}$$

This process is repeated for all industries and regions for the fossil fuel, intermediate, and materials nests. The top production nest is calibrated in a similar fashion. There is no need to set an elasticity for this nest since it is Cobb-Douglas. The ω_n^j parameter is set as the share of materials input in production for industry j in region n. I then set prices to unity and solve for the scale parameter:

$$\gamma_{np}^{j} = \omega_n^j \left(\frac{\omega_n^j}{1-\omega_n^j} \right)^{\omega_n^j - 1}$$

Table A.3: Countries and Associated Regions

Abbreviation	Name	Region
AUS	Australia	Rest of the World
AUT	Austria	Europe
BEL	Belgium	Europe
BGR	Bulgaria	Europe
BRA	Brazil	Rest of the World
CAN	Canada	North America
CHN	China	China
CYP	Cyprus	Europe
CZE	Czech Republic	Europe
DEU	Germany	Europe
DNK	Denmark	Europe
ESP	Spain	Europe
EST	Estonia	Europe
FIN	Finland	Europe
FRA	France	Europe
GBR	United Kingdom	Europe
GRC	Greece	Europe
HUN	Hungary	Europe
IDN	Indonesia	Rest of the World
IND	India	Rest of the World
IRL	Ireland	Europe
ITA	Italy	Europe
JPN	Japan	Rest of the World
KOR	Republic of Korea	Rest of the World
LTU	Lithuania	Europe
LUX	Luxembourg	Europe
LVA	Latvia	Europe
MEX	Mexico	Rest of the World
MLT	Malta	Europe
NLD	Netherlands	Europe
POL	Poland	Europe
PRT	Portugal	Europe
ROU	Romania	Europe
RUS	Russia	Rest of the World
SVK	SlovakRepublic	Europe
SVN	Slovenia	Europe
SWE	Sweden	Europe
TUR	Turkey	Rest of the World
TWN	Taiwan	Rest of the World
USA	UnitedStates	United States

The first set of household parameters are those that govern consumption of goods, θ_n^j, which is the share parameter on good j for the household in region n. These are simply consumption shares from the WIOD. Define $\hat{c}_n^j$ as the observed real consumption level of good j by region n. Then set the share parameter

$$\theta_n^j = \frac{\hat{c}_n^j}{\sum_{i=1}^J \hat{c}_n^i}$$

The labor-leisure elasticity parameter ν is set exogenously from the literature. To get the scale parameter I first need to set a total labor supply. For this, I set the labor supply as equal to total income for the region. Then using the supply of labor observed in the data, $\hat{l}_n$, I set the scale parameter as:

$$\mu_n = \frac{1}{(\bar{L}_n - l_n)^{\frac{1}{\nu}}}$$

While I use a single elasticity value for the world in this example, in the application these can vary by industry and region. I do this in the last section of the robustness checks.

The last step is to calibrate the table of carbon coefficients. This is done by first connecting emissions data from the environmental satellite accounts to fuel consumption data. Define $\hat{Q}_n^f$ as the total amount of fuel f consumed by region n measured in billions of \$US, and define $\hat{E}_n^f$ as the total emissions by region n from fuel source f measured in gigatons (one million tons) of CO_2. The carbon coefficient for this region's fuel is defined as

$$cc_n^f = \frac{\hat{E}_n^f}{\hat{Q}_n^f}$$

This gives the gigatons of CO_2 that are emitted on average when one unit of fuel f is consumed. Carbon coefficients are reported in Table A.6.

A.3 Monte Carlo Simulation

In the robustness section of the paper, I randomly draw parameter values to create a grid to search over. For each variable, I draw a value from a uniform distribution within a specified range. For production elasticities and the leisure elasticity, I choose a range between -50% and +50% of the baseline value. This covers most of the estimates that have been found in the literature. The sector elasticity is varied between 0 and 2. This covers the range of estimates I found using regression, as well as the possibility of 0, which is perfectly immobile labor. The carbon coefficients are varied by fuel type, and the range of possible values is between the maximum and minimum values for each fuel type. The parameters chosen and their respective ranges are reported in Table A.4.

Table A.4: Ranges for Randomization of Parameter Values

Parameter	Range Min	Range Max
Materials elasticity	0.485	1.455
Intermediate elasticity	0.44	1.32
Fossil fuel elasticity	0.535	1.605
Sector elasticity	0	2
Leisure elasticity	0.25	0.75
Coal carbon coefficient	0.0200	0.0310
Natural gas carbon coefficient	0.0030	0.0073
Refined Petroleum carbon coefficient	0.0024	0.0050

Table A.5: Trade Elasticities

Industry	Hertel et. al. (2007)	Caliendo and Parro (2015)
Coal Extraction	6.0	15.7
Oil Extraction	10.4	15.7
Natural Gas Extraction	34.4	15.7
Agriculture	5.7	8.1
Mining	1.8	15.7
Goods Manufacturing	6.4	7.0
Petroleum Refining	4.2	51.1
Chemical Manufacturing	6.6	3.2
Other Manufacturing	7.4	6.3
Utilities	7.0	4.6
Construction	7.0	4.6
Consumer Services	7.0	4.6
Transportation	7.0	4.6
Business Services	7.0	4.6
Social Services	7.0	4.6

Table A.6: Carbon Coefficients

Region	Coal	Petroleum	Natural Gas
China	0.03098	0.00365	0.00344
Europe	0.02071	0.00236	0.00723
North America	0.02389	0.00385	0.00731
United States	0.02986	0.00368	0.00495
Rest of the World	0.01997	0.00505	0.00295

Table A.7: Example of a Transportation Matrix for Goods Manufacturing Industry

	China	Europe	North America	United States	Rest of the World	Total Demand
China	$2,555.96	$20.64	$5.05	$10.87	$57.91	$2,650.43
Europe	$74.66	$1,992.65	$4.22	$18.22	$201.08	$2,290.84
North America	$14.06	$10.61	$358.21	$47.27	$24.37	$454.52
United States	$64.10	$37.38	$46.90	$1,343.19	$125.74	$1,617.31
Rest of the World	$211.02	$246.37	$15.33	$59.65	$4,126.08	$4,658.44
Total Supply	$2,919.80	$2,307.66	$429.71	$1,479.20	$4,535.17	

Notes: Each row presents the demand from the region in the first column that is supplied by the region in the header row. All entries are in Billions of $US.

Appendix B: Empirical Validation of the Gravity Algorithm

The question might now be asked, how well does my gravity algorithm fit the data? In this section I use the dataset from the WIOD to test how well the model predicts trade flows given data on consumption and production. Note that in this section I will not be using the full CGE model described. Instead, I am using production and consumption amounts observed in the data to predict trade flows between countries. When I run the policy simulations later in the paper, these numbers will come from the CGE model to predict trade flows in the counterfactual equilibrium.

The gravity model I describe outputs a transportation polytope, which by construction also describes a joint probability function. If I use the marginal probabilities of consumption and production, then the function is such that it takes in two marginal probability density functions (PDF) and outputs a discrete joint probability function.

$$P_{in}^{j} = C(f^{j}(d_i^{j}), f^{j}(s_n^{j}); \mathbf{A}^{\mathrm{j}})$$

Here P_{in}^{j} is the probability that a given good j is traded between origin n and destination i. This probability is a function of the PDF of demand in the destination $f^{j}(d_i)$, the PDF of supply in the origin $f(s_n)$, and a matrix of parameters $\mathbf{A}^{j}$. Each element of the matrix is calculated as:

$$a_{nz}^{j} = \frac{X_{in}^{j(t)}}{\bar{X}_{i}^{j(t)}}$$

Which is just the share of destination i's consumption of good j that comes from origin n. I calculate this parameter using data for a given year t. For the primary specification, I use the year prior to the year I am estimating (i.e., if I was predicting trade flows in year t, I use a matrix parameterized in year $t-1$). Using this setup, I predict P_{in}^{j} and multiply the predicted probabilities by total consumption (or production), which gives the predicted trade flow from region n to region i.

$$\hat{X}_{in}^{j} = \hat{P}_{in}^{j} \times \sum_{q=1}^{N} d_q^j$$

The Armington model is specified as the following regression equation from Feenstra et al. (2018), which is essentially the same form used in Armington (1969).

$$\ln\left(\frac{X_{in}^{j}}{X_{i(home)}}\right) = Y_{in}^{j} = \beta_0 + \sum_{j=1}^{J}\sum_{i=1}^{N}\beta_i^j\left(\frac{P_n^j}{P_{i(home)}^j}\right) + \gamma_i + \phi_n + \theta_j + \epsilon$$

Here X_{in}^{j} is the trade flow of good j from origin n to destination i and $X_{i(home)}^{j}$ is total consumption of good j from home in destination i. P_n^j is the price of good j from origin n, and $P_{i(home)}^j$ is the home price of good j in destination i. The remaining terms, γ_i, ϕ_n, and θ_j are fixed effects by destination, origin, and good type, respectively. The Armington elasticity, σ_i^j, can be calculated as $\sigma_i^j = 1 - \beta_i^j$.

The equation above is estimated using regression and, then using the same data, I predict $\hat{Y}_{in}^{j}$ and use this to predict trade flows.

$$\hat{X}_{in}^{j} = \exp\left(\hat{Y}_{in}^{j}\right) X_{i(home)}$$

$\hat{X}_{in}^{j}$ is the predicted trade flow and $X_{i(home)}$ is the home consumption observed in the dataset.

To create Figure 2.2, I use the Armington model set forth here to predict the trade flows in the data. In the in-sample panel, this uses all years included in the dataset. In the out-of-sample panel, I use data from 1995 through 2000 to estimate the coefficients in the model. I then used these estimates to predict trade flows in 2011. The gravity model is the same. I use the empirical version of the gravity model I developed above to predict trade flows. In the in-sample model, I use the data from the year directly prior to generate $\mathbf{A}^{j}$ and predict a given year's trade flows. To create the out-of-sample model, I use data from 2000 to generate $\mathbf{A}^{j}$ and predict trade flows in the year 2011.

Table B.1: Mapping Between WIOD Industries and WITS Commodities

WIOD Industry	WITS Industry
Agriculture, Hunting, Forestry and Fishing	Animal
Mining and Quarrying	Minerals
Food, Beverages and Tobacco	Food Products
Textiles and Textile Products	Textiles and Clothing
Leather, Leather and Footwear	Footwear
Wood and Products of Wood and Cork	Wood
Pulp, Paper, Printing and Publishing	Miscellaneous
Coke, Refined Petroleum and Nuclear Fuel	Fuels
Chemicals and Chemical Products	Chemicals
Rubber and Plastics	Plastic or Rubber
Other Non-Metallic Mineral	Stone and Glass
Basic Metals and Fabricated Metal	Metals
Machinery, Nec	Mach and Elec
Electrical and Optical Equipment	Mach and Elec
Transport Equipment	Transportation
Manufacturing, Nec; Recycling	Miscellaneous
Electricity, Gas and Water Supply	Utilities and Construction
Construction	Utilities and Construction
Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	Consumer goods
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	Consumer goods
Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	Consumer goods
Hotels and Restaurants	Consumer Services
Inland Transport	Transportation
Water Transport	Transportation
Air Transport	Transportation
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	Transportation
Post and Telecommunications	Transportation
Financial Intermediation	Business Services
Real Estate Activities	Business Services
Renting of M&Eq and Other Business Activities	Business Services
Public Admin and Defence; Compulsory Social Security	Consumer Services
Education	Consumer Services
Health and Social Work	Consumer Services
Other Community, Social and Personal Services	Consumer Services
Private Households with Employed Persons	Consumer Services

Notes: This table shows how industry categories in WIOD were matched to commodity categories in WITS.

Appendix C: Model of Sick Leave

Suppose a sick leave program works like this: each year a worker is allocated a specified number of paid sick days (possibly based on seniority) which often accrue year over year. Allowing employees to bank their sick days is sometimes called "carry-over." If the employee gets sick, they can still get their wage, but it reduces the number of sick days in their sick leave bank. When the employee quits or retires, then the employer might pay them for unused days in their sick leave bank. This policy likely varies widely by company and is called a "cash-out" rule. I do not know how many sick leave programs allow carry-over and cash-out since I have not found statistics of the specific clauses of companies. I am mainly using anecdotal evidence to derive these rules. However, there may be an employer incentive to set up sick leave in this manner. If employees have several sick days and were about to lose them, then they have a strong incentive to take them all at one time before leaving. Employers might prefer to avoid this clumping of absenteeism, and may offer some benefit to be paid for sick days.

Now I turn to the strategic decision of an agent facing the above paid sick leave regime. Suppose a worker works for two periods and has one period of paid sick leave. He wakes up the first period and is given a draw - healthy (H) or sick (S), and he is sick with some probability θ. He can then choose to attend (A) work anyway, or he can choose to take his sick day (D). If he attends work sick ,he pays some cost (P) which could include utility loss from being miserable at work or some medical intervention. If he chooses to stay home from work in period 1, he uses his sick day. If he gets sick again in period two and stays home, he receives no wage for that period. Finally, if he goes to work in period one he receives w_1. In period two he receives w_2, and If he has not used his sick day, then he will cash it out for an additional benefit b.

I can solve this simultaneous game by first finding the optimal decision in period 2. First I assume that a healthy worker always attends (he does not shirk/play hooky). Consider a worker who gets sick in period 1. If he uses his sick day, he arrives in period 2 with no sick day banked. If he gets sick again, he will only attend work if Eq. 1 is true.

$$w_2 > P_2 \tag{1}$$

If he attended work while sick in period 1 then he arrives in period 2 with a sick day banked. If he gets sick again, he only attends work if it is worth it to get the benefit or if Eq. 2 is true.

$$b > P_2 \tag{2}$$

Note that if $b = 0$ then he will always take his sick day if he is sick. Additionally, notice that a worker without paid sick leave will attend work if Eq. 1 is true regardless of what happened in period 1. Now assume that $b < w_2$ and that $P_2 \sim U(\underline{P}, \overline{P})$. So, I can divide up the distribution of costs like this

$$\Pr(b < w_2 < P_2) = \beta^H$$

$$\Pr(b < P_2 < w_2) = \beta^M$$

$$\Pr(P_2 < b < w_2) = \beta^L$$

$$\beta^H + \beta^M + \beta^L = 1$$

These are the probabilities of getting high (H), middle (M), and low (L) costs respectively. So, a person with paid sick leave in the second period has a lower probability of attending work than a worker without paid sick leave. If a worker with paid sick leave gets sick in the first period and attends work, his expected payoff from getting sick in the second period is:

$$(w_1 - P_1) + w_2 + \beta_L(b - P_2) \tag{3}$$

If he is healthy in the second period he gets

$$w_1 - P_1 + w_2 + b \tag{4}$$

So, the expected payout from attending work in period 1 is found by taking the expectations of the payouts in equations 3 and 4. This reduces to:

$$E(A) = w_1 - P_1 + w_2 + b + \theta[\beta_L(b - P_2) - b] \tag{5}$$

Now consider the same worker decides to take his sick day in period 1. If he gets sick in period 2 again, then his expected value from being sick is:

$$w_1 + (1 - \beta_H)(w_2 - P_2) \tag{6}$$

If he is healthy he gets his wages for both periods:

$$w_1 + w_2 \tag{7}$$

The expected payout from taking a sick day in period one is then the expectation over payouts in equations 6 and 7.

$$E(D) = w_1 + \theta[(1 - \beta_H)(w_2 - P_2)] \tag{8}$$

I can now find the optimal decision for a sick worker in period 1. This worker will attend work in period 1 if equation 5 minus equation 8 is greater than zero. Using this I get the rule that a sick worker will attend work in period 1 if

$$P_1 < w_2 + b + \theta[\beta_L(b - P_2) - (1 - \beta_H)(w_2 - P_2) + w_2 - b] \tag{9}$$

I again assume that $P_1 \sim U(\underline{P}, \overline{P})$, so that the probability of attending work is the probability that the worker in the first period gets a cost lower than the right-hand side of equation 9. Since this is drawn from a uniform distribution, the probability of attending work sick falls as the right-hand side decreases.

To simplify equation 9, I will look at the limiting case where there is no cash-out option (b = 0). So now equation 9 becomes

$$P_1 < w_2 + \theta[w_2 - (1 - \beta_H)(w_2 - P_2)] \tag{10}$$

Now consider a policy that *decreases* θ. In the context of this paper ,this is a policy that reduces pollution and the likelihood of getting sick. The term in brackets on the right-hand side is positive since the worker will only attend work if they get $P_2 < w_2$. However, this means that a decrease in θ leads to a decrease in the probability of attending work in period 1. This conclusion is the thrust of my argument. If the risk of getting sick in the future is lower, then the benefit to attending work and saving a sick day is lower as well. So, workers with paid sick leave may be more likely to take sick days if the probability of getting sick in the future falls.

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Vita

Kenneth Austin Castellanos grew up in Rome, GA and later started college at Clayton State University before transferring to and graduating from Georgia State University with a Bachelor of Business Administration degree in Economics. After graduating, he worked at Cobb County School District as a budget technician and took classes in the evening. During this time, he was also a research assistant for the Center for State and Local Finance and worked on state models of tax changes.

Kenneth started his PhD program in 2016 focusing on computable general equilibrium research and worked on a grant from the Alliance for Market Solutions studying employment effects from climate policy. He later received a fellowship from the Federal Reserve Bank of Atlanta, working on international labor issues. He taught introductory microeconomics and macroeconomics at both Georgia State University and Berry College. He was awarded the E. D. "Jack" Dunn fellowship for research in public finance and regulatory issues. He has now accepted a position as an analyst for the Congressional Budget Office in Washington D.C.